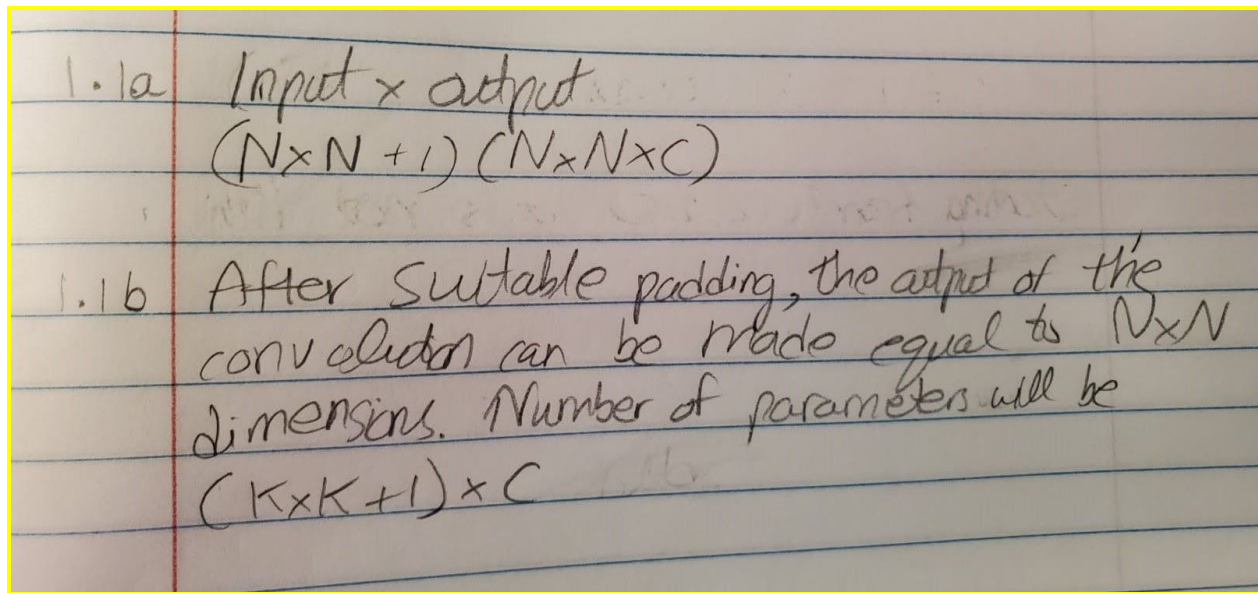


## 1. Convolutional Neural Networks [40 points]

### 1.1.



### 1.2.

#### Output from CNN\_Template.py

Train Epoch: 0 Loss: 2.297700  
Train Epoch: 0 Loss: 1.196974  
Train Epoch: 0 Loss: 0.879102  
Train Epoch: 0 Loss: 0.631757  
Train set Accuracy: 93.1%  
Test set Accuracy: 92.8%

Train Epoch: 1 Loss: 0.489871  
Train Epoch: 1 Loss: 0.481325  
Train Epoch: 1 Loss: 0.555330  
Train Epoch: 1 Loss: 0.275723  
Train set Accuracy: 95.5%  
Test set Accuracy: 95.0%

Train Epoch: 2 Loss: 0.295671  
Train Epoch: 2 Loss: 0.565036  
Train Epoch: 2 Loss: 0.677427

Train Epoch: 2 Loss: 0.511953  
Train set Accuracy: 96.6%  
Test set Accuracy: 95.7%

Train Epoch: 3 Loss: 0.419044  
Train Epoch: 3 Loss: 0.362855  
Train Epoch: 3 Loss: 0.424028  
Train Epoch: 3 Loss: 0.605251  
Train set Accuracy: 97.0%  
Test set Accuracy: 96.2%

Train Epoch: 4 Loss: 0.290133  
Train Epoch: 4 Loss: 0.524181  
Train Epoch: 4 Loss: 0.262745  
Train Epoch: 4 Loss: 0.562951  
Train set Accuracy: 96.8%  
Test set Accuracy: 95.7%

Train Epoch: 5 Loss: 0.470912  
Train Epoch: 5 Loss: 0.643341  
Train Epoch: 5 Loss: 0.385698  
Train Epoch: 5 Loss: 0.815582  
Train set Accuracy: 97.9%  
Test set Accuracy: 96.5%

Train Epoch: 6 Loss: 0.110166  
Train Epoch: 6 Loss: 0.386724  
Train Epoch: 6 Loss: 0.626907  
Train Epoch: 6 Loss: 0.300639  
Train set Accuracy: 97.9%  
Test set Accuracy: 96.6%

Train Epoch: 7 Loss: 0.245308  
Train Epoch: 7 Loss: 0.248199  
Train Epoch: 7 Loss: 0.602157  
Train Epoch: 7 Loss: 0.261321  
Train set Accuracy: 98.2%  
Test set Accuracy: 96.7%

Train Epoch: 8 Loss: 0.263233  
Train Epoch: 8 Loss: 0.242980  
Train Epoch: 8 Loss: 0.320146  
Train Epoch: 8 Loss: 0.397581

Train set Accuracy: 97.2%

Test set Accuracy: 95.8%

Train Epoch: 9 Loss: 0.449104

Train Epoch: 9 Loss: 0.264772

Train Epoch: 9 Loss: 0.233881

Train Epoch: 9 Loss: 0.552281

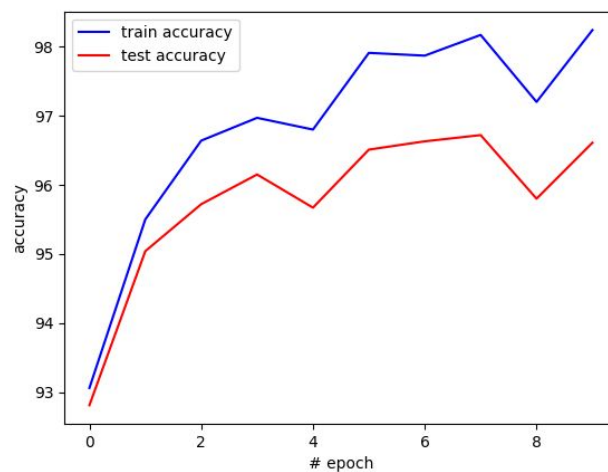
Train set Accuracy: 98.2%

Test set Accuracy: 96.6%

### 1.2.a

o/p size	#Params
[26x26x32]	320
[24x24x64]	18496
[12x12x64]	0
[12x12x64]	0
[9216]	0
[128]	1179776
[128]	0
[10]	1290

### 1.2.b



## 1.2.c

$$\begin{aligned} 2.c \quad \text{params in convolutional layer} &= 320 + 18496 = 18816 \\ \text{params in fully connected layer} &= 1179776 + 1290 = \\ &= 1181066 \end{aligned}$$

$$\text{Fraction of conv} = \frac{18816}{1181066 + 18816} = 0.015681542$$

$$\text{fraction of FCL} = \frac{1181066}{1199882} = 0.984318458$$

Not surprising. As we know that a convolution layer having kernel-dimension gives us a fully connected layer. We reduce the dimensions of maps in convolution due to which we end up having minimum weight and memory as compared to fully connected layer.

## 2. Singular Value Decomposition [40 points + 10 Extra Credit]

### 2.1

```
def SVD(A, s, k):
    # TODO: Calculate probabilities p_i
    n,m = A.shape
    probabilities = list()
    counter = 0
    while counter < n:
        upper = math.pow(np.linalg.norm(A[counter,:], ord=2), 2)
        lower = math.pow(np.linalg.norm(A), 2)
        probabilities.append(upper / lower)
        counter += 1

    # TODO: Construct S matrix of size s by m
    S = np.zeros((s,m))
    counter = 0
    while counter < s:
        random_choice = np.random.choice(list(range(n)), p=probabilities)
        S[counter] = A[random_choice,:]
        counter += 1

    # TODO: Calculate SS^T
    ss_to_t = np.matmul(S, S.T)

    # TODO: Compute SVD for SS^T
    svd = np.linalg.svd(ss_to_t)
    W = svd[0]
    values = svd[1]

    # TODO: Construct H matrix of size m by k
    H = np.zeros((k, m))
    counter = 0
    while counter < k:
        mat_mul = np.matmul(S.T, W[:, counter])
        linalg_norm = np.linalg.norm(mat_mul, ord=2)
        H[counter] = mat_mul / linalg_norm
        counter += 1

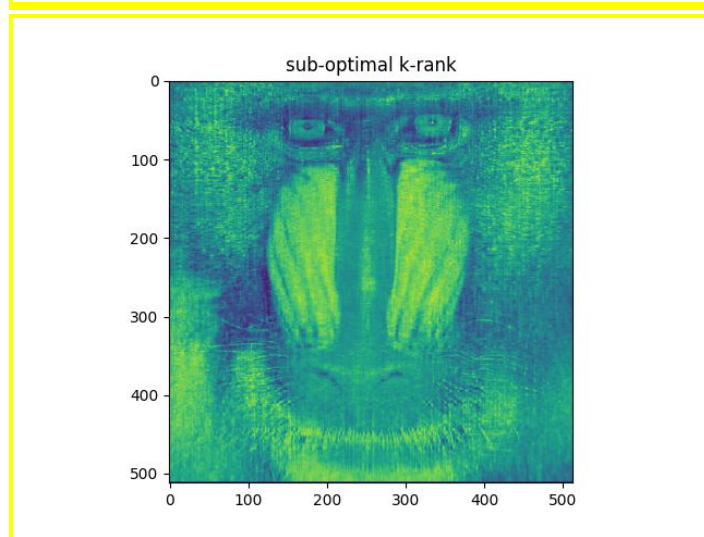
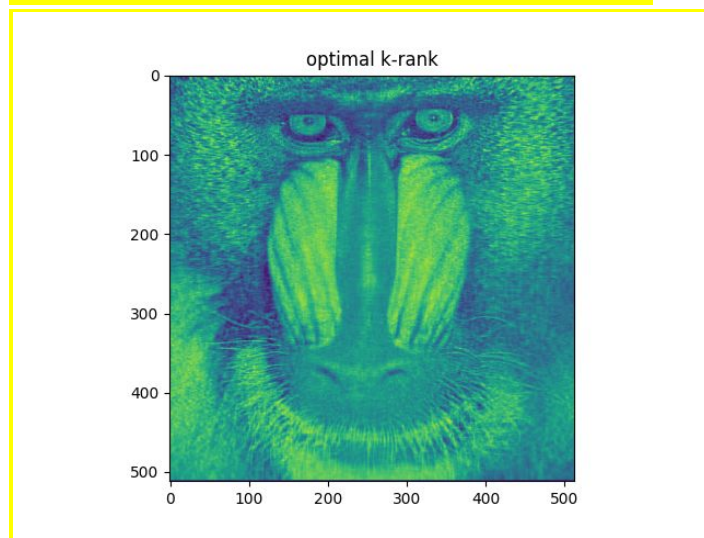
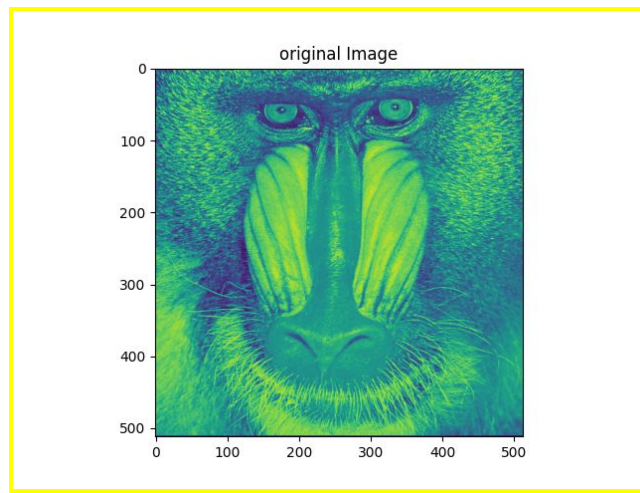
    values.sort()
    values = values[::-1]
    top_k_singular_values_sigma = values[:k]

    # Return matrix H and top-k singular values sigma
    return H.T, top_k_singular_values_sigma
```

## 2.2 EXTRA CREDIT

### 2.3

#### 2.3a



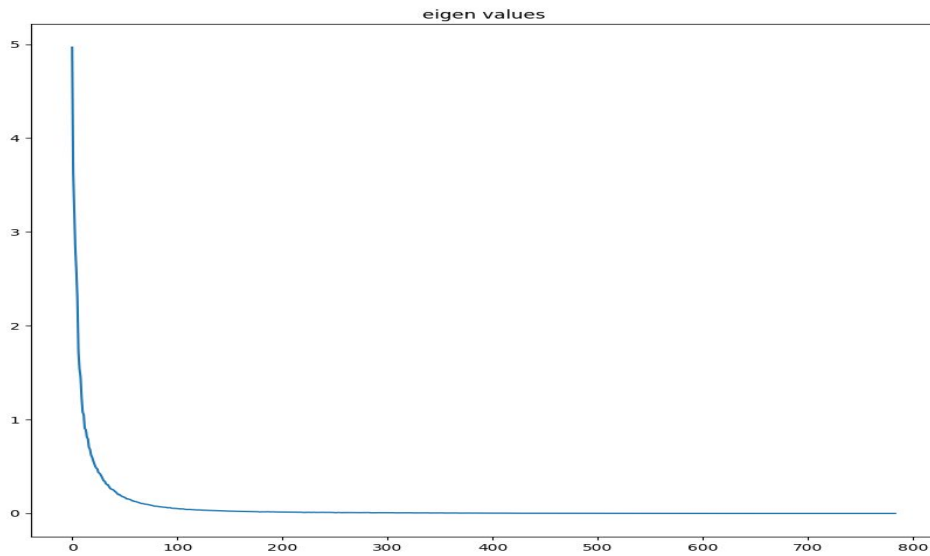
2.3b

8827.532897298843  
11399.808798648595

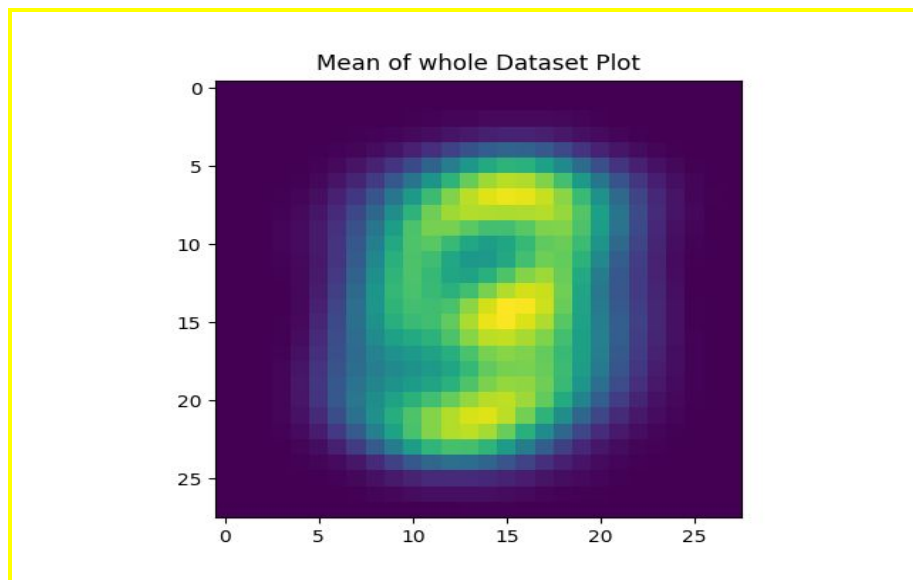
### 3. Principle Component Analysis [20 points]

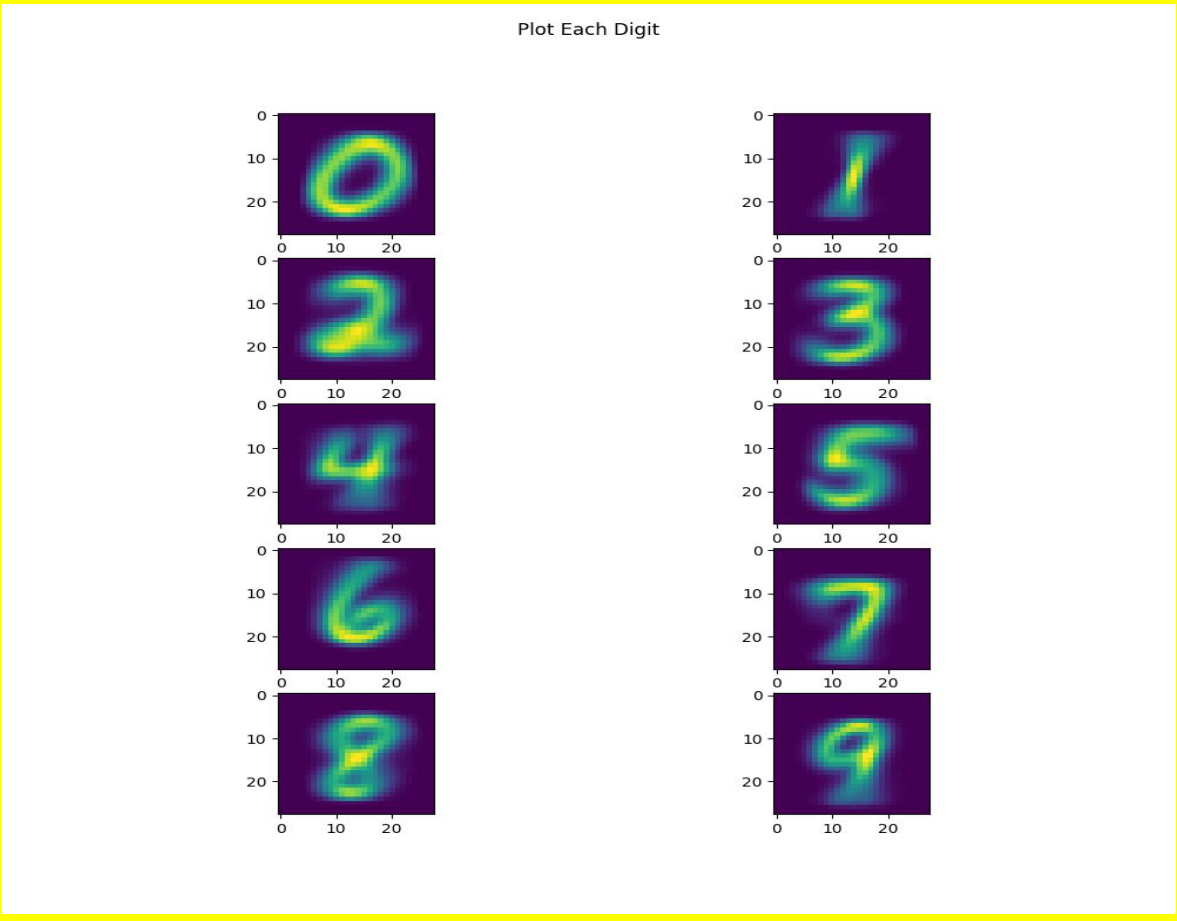
3.1

I will use 30 because after that the eigenvalues were insignificant.

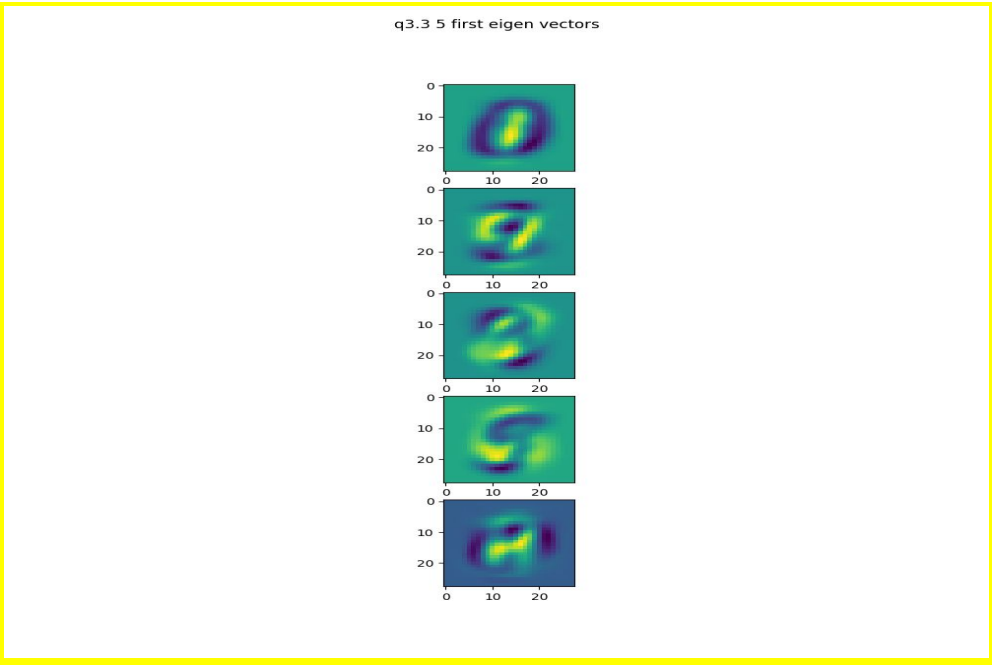


3.2





3.3

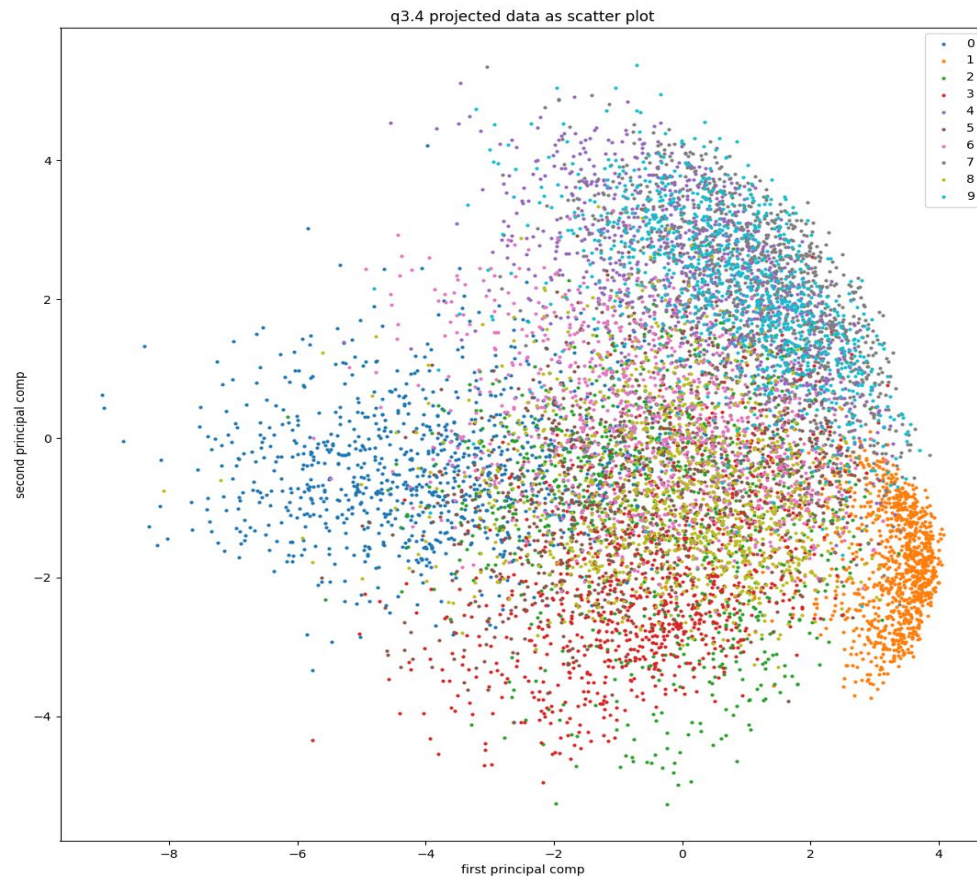


0, 9, 3, 5, 2



### 3.4

Digit 7 and 9 are close to each other. The number 8 is scattered in the center as it has similarity to most of the digits



### Sources

<https://www.learnopencv.com/number-of-parameters-and-tensor-sizes-in-convolutional-neural-network/>