ASSIGNMENT - 4

ML REPORT

SECTION - A

Ques - (a)

- An input image of dimensions M×N with P channels.
- A kernel of size K x K.
- A stride of 1 and no padding.

For a convolution operation with a stride of 1 and no padding, the dimensions of the resulting feature map can be determined by:

Output Height=M-K+1

Output Width=N-K+1

Thus, the dimensions of the output feature map will be:

 $(M-K+1)\times(N-K+1)$

Ques - (b)

To compute the number of elementary operations needed for a single output pixel of the feature map:

- 1. Multiplications: Each element of the K×K kernel is multiplied by a corresponding element in the input image's K×K patch. Since the input image has P channels, and the kernel must apply to each channel, this results in: K×K×P multiplications for each output pixel.
- 2. Additions: After the multiplications, the products are summed together to compute the output value. Each channel's K×K patch results in K×K-1 additions per channel, and since there are P such channels: (K×K-1)×P Additionally, after summing within the channels, the sums from each of the P channels need to be added together to get a single output value. This would add: P-1 more additions.

Thus, the total number of additions is: $(K \times K - 1) \times P + (P - 1)$

Therefore, the total number of elementary operations (multiplications and additions) required to compute a single output pixel is:

$$K \times K \times P(multiplications) + ((K \times K-1) \times P + P - 1)(additions)$$

Ques - (c)

General Time Complexity: The total number of operations for the forward pass is proportional to the number of output pixels times the number of operations per pixel. Therefore, the computational time complexity is:

$$O((M-K+1)(N-K+1)\times(Q\times K^2\times P)$$

2. **Assuming min (M,N)** \gg **K**: When K is much smaller than M and N, $(M-K+1)\approx M$ and $(N-K+1)\approx N$. The time complexity simplifies to: $O(MN\times Q\times K^2\times P)$

Part (B)

K-Means Algorithm: Key Steps

- 1. Assignment Step: Each data point is assigned to the nearest cluster centroid based on Euclidean distance.
- 2. Update Step: Recalculate each cluster's centroid by taking the mean of all data points assigned to that cluster.

Determining Optimal Number of Clusters: Elbow Method

• Elbow Method: Plot the total within-cluster sum of squares (WCSS) against different numbers of clusters (k) and look for the 'elbow' where the reduction in WCSS slows down, indicating the optimal k.

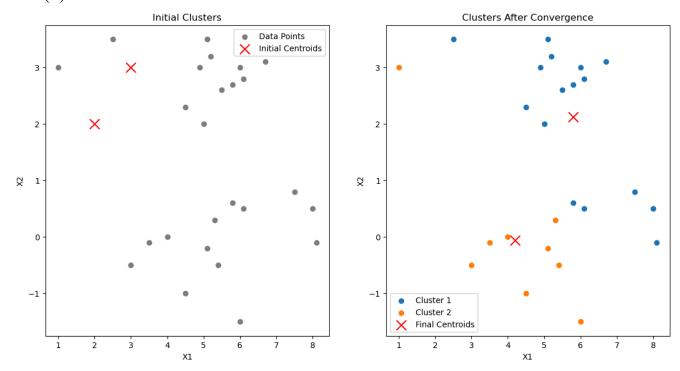
Random Assignment of Cluster Centroids:

- Random Assignment: Starting centroids are placed randomly.
- Global Minima: Random starting points typically lead to convergence to a local minimum rather than a global minimum. Multiple runs with different initializations are recommended to approach the global minimum more closely.

SECTION - B

Part (a) In the notebook

Part (b)

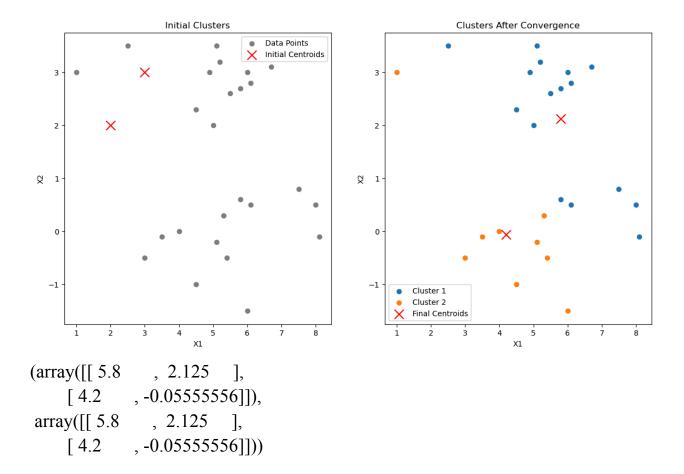


Final centroids:

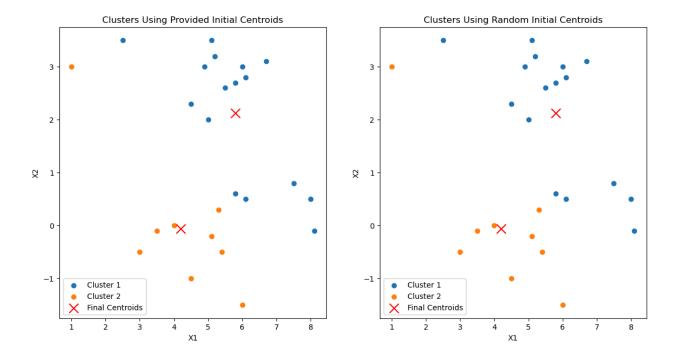
[[5.8 2.125]

[4.2 -0.05555556]]

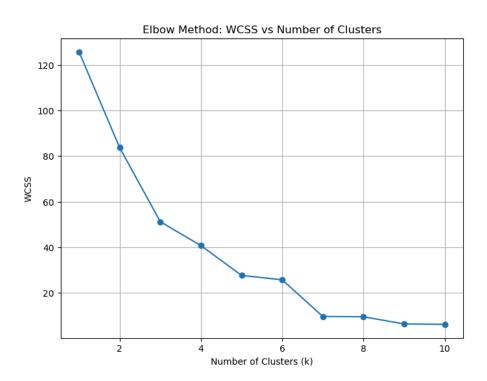
Cluster assignments:

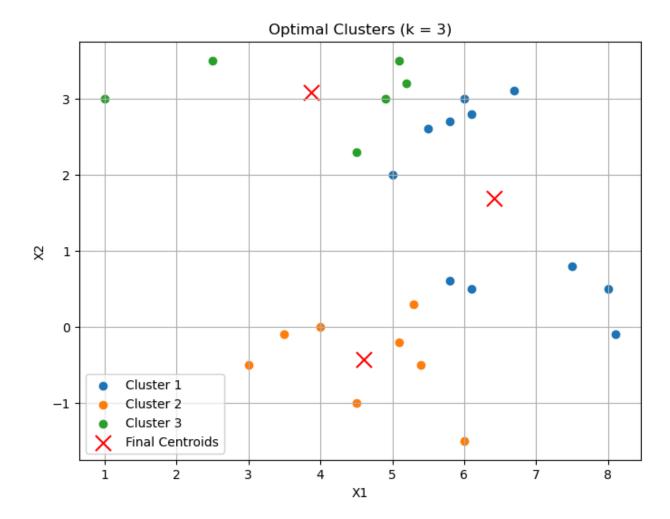


Part (c)



Part (d)





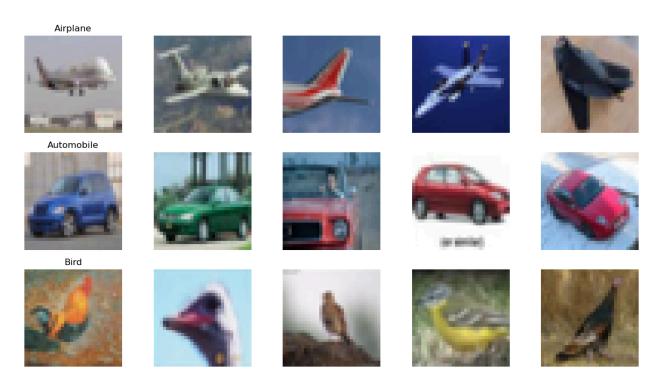
SECTION - C

Dataset:

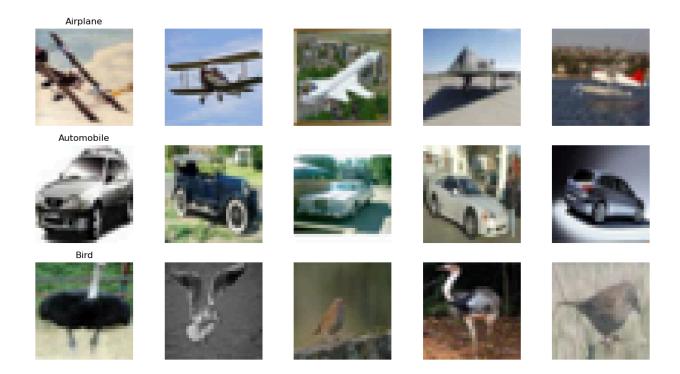
Train dataset: Total images = 12000
Validation dataset: Total images = 3000

Test dataset: Total images = 3000

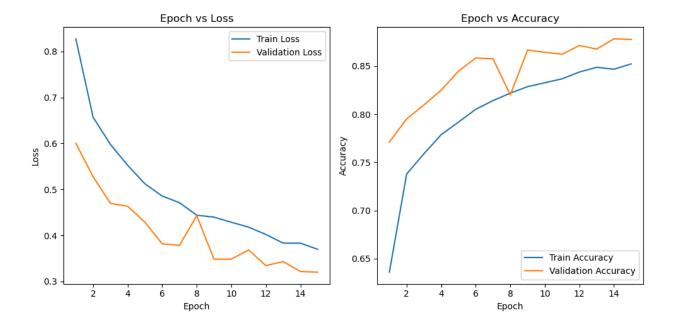
Training Dataset Images:



Validation Dataset Images:

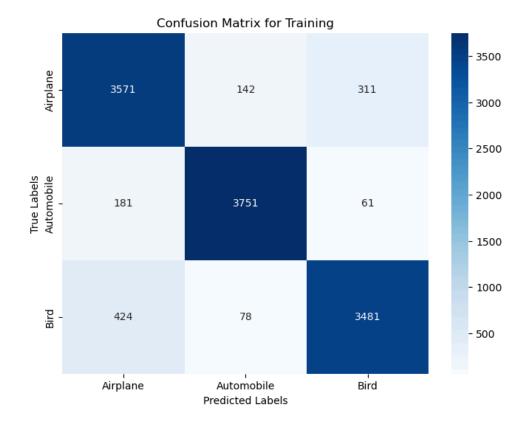


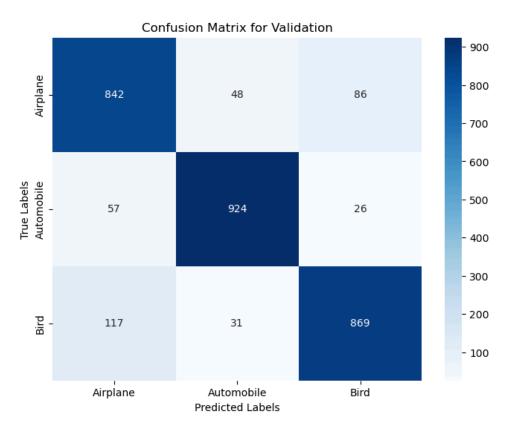
4.

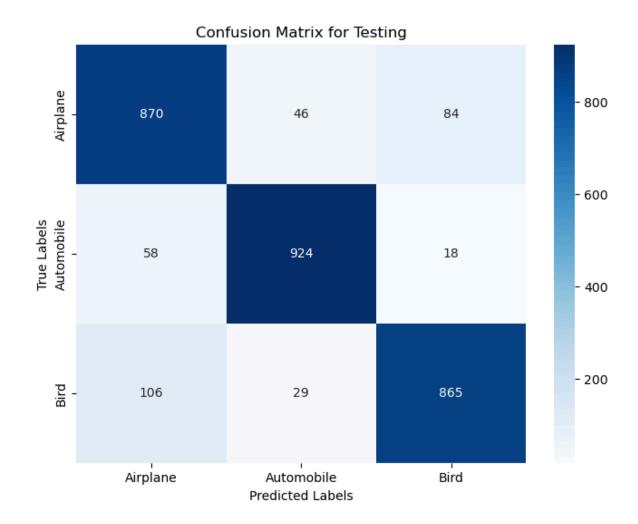


5.
Best Model Path: models/model_epoch_14.pth with Validation Accuracy:
0.8783

Test Accuracy: 0.8863
Test F1 Score: 0.8865







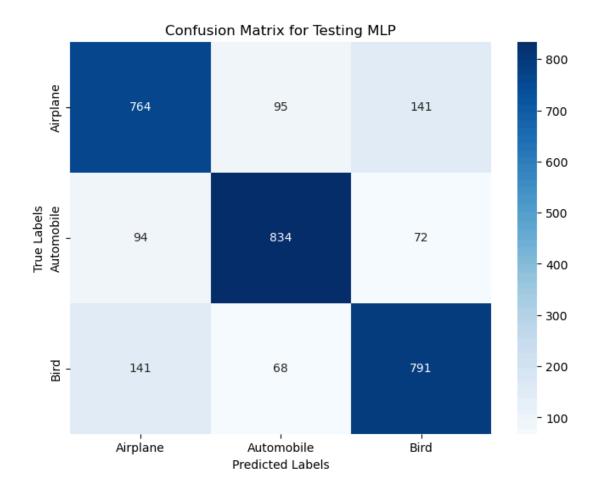
6.



Best MLP Model: Epoch 15 with Validation Accuracy: 0.7835

MLP Test Accuracy: 0.7963 MLP Test F1 Score: 0.7964

7.



Comparison Results:

Accuracy - CNN: 0.8500, MLP: 0.7963 F1 Score - CNN: 0.8400, MLP: 0.7964