

report_2022266

Section A

SECTION - APART - A

(a) We took stride=1 and padding=0.

\therefore Both height(M) & width(N) will be reduced by,

$$\text{Output height} = 1 + M - K$$

$$\text{Output width} = 1 - K + N$$

$$\Rightarrow \text{Result feature map dimension} = (1 + M - K) \times (1 - K + N)$$

(b) For a single pixel in output feature map:

(1) Kernel of size ~~size~~ $K \times K$ spans K^2 positions in the input image.

Each kernel element performs:

- one multiplication with the corresponding input pixel. A total of K^2 multiplications.

(2) Results of K^2 multiplications are summed up to produce a single output pixel. This requires $K^2 - 1$ additions.

(3) ~~size~~ If input image has P channels, kernel will span all channels. \therefore Total no. of ops.

- Multiplication - $P \times K^2$

- Addition - $P \times K^2 - 1$

(4) Total Mul - $P \times K^2$

Total Add - $P \times K^2 - 1$

$$\therefore \text{Total Op} = P \times K^2 + P \times K^2 - 1$$

$$\Rightarrow P \times 2K^2 - 1$$



© To analyze computational T.C. of forward pass with Q kernels, \therefore

~~No. of~~ From (a), resulting feature map dimensions for a single kernel are: $(M-K+1) \times (N-K+1)$.
Thus, total output pixels in feature map:
No. of output pixels = $(M-K+1)(N-K+1)$.

From (b), cost to compute one output pixel for a single kernel is: -

$$\text{Cost for 1 pixel} \Rightarrow P \times 2K^2 - 1$$

For a single kernel, Total cost is the cost per pixel multiplied by no. of pixels: -

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

$$\text{Cost for } Q \text{ kernel} = Q \times (M-K+1) \times (N-K+1) \times P \times 2K^2 - 1$$

Considering $M \times N$ are large,

$$\Rightarrow \text{T.C.} = O(Q \times P \times K^2 \times M \times N)$$

Now assuming $\min(M, N) \gg K$:

$$\Rightarrow \text{T.C.} = O(Q \times P \times M \times N)$$

① Assignment Step:

Using Euclidean dist: $\text{Cluster}(x_i) = \underset{k}{\operatorname{argmin}} \|x_i - \mu_k\|^2$

② Update step:

After assigning all points to clusters, the centroids are updated by finding mean of all points assigned to each cluster:

$$\mu_k = \frac{1}{n_k} \sum_{x_i \in C_k} x_i$$

We repeat these steps until centroids stop changing or assignment stabilises.

Elbow Method -

- ① Run K-Means Algo for various values of k .
- ② For each k , compute inertia.
- ③ Plot inertia versus k .
- ④ Look for elbow point, where the decrease in inertia slows significantly.

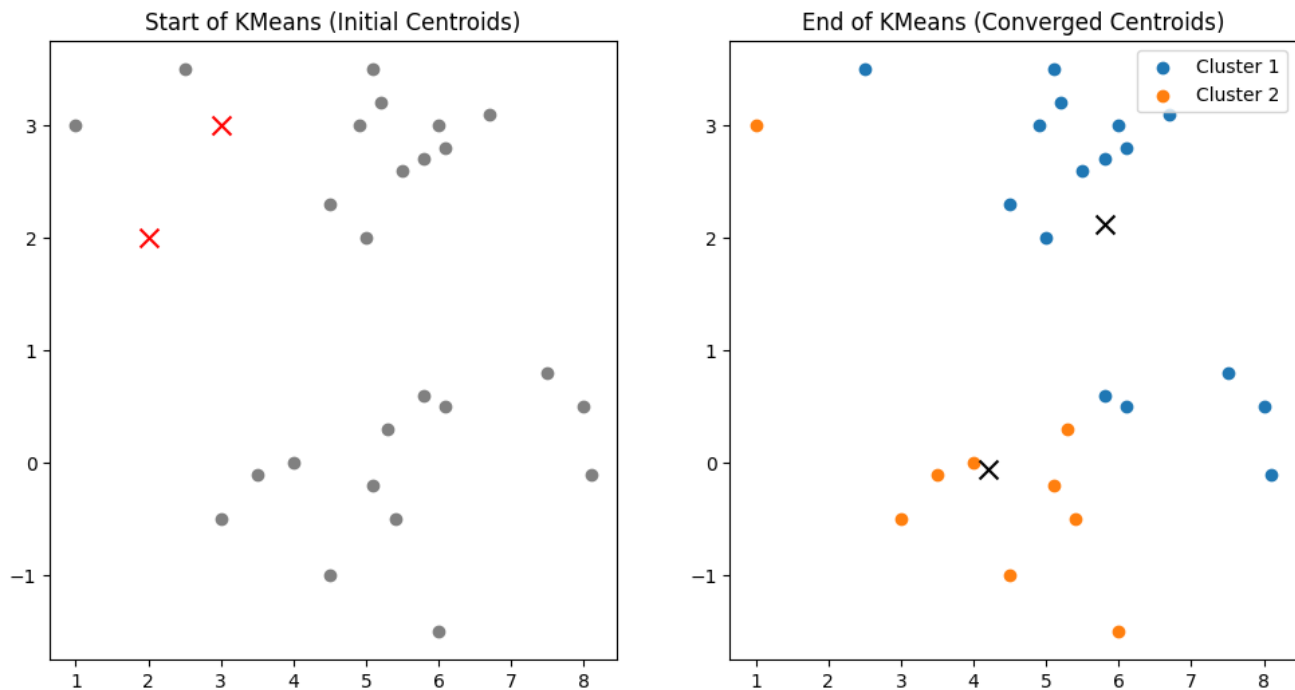
No, it isn't guaranteed that random initialization of centroids can lead to Global Minima.
We can use K-Means++ for this.

Section B

1. Implement the k-means clustering : Initialization, Assignment, Update, Convergence Check (convergence threshold of $1e-4$.)

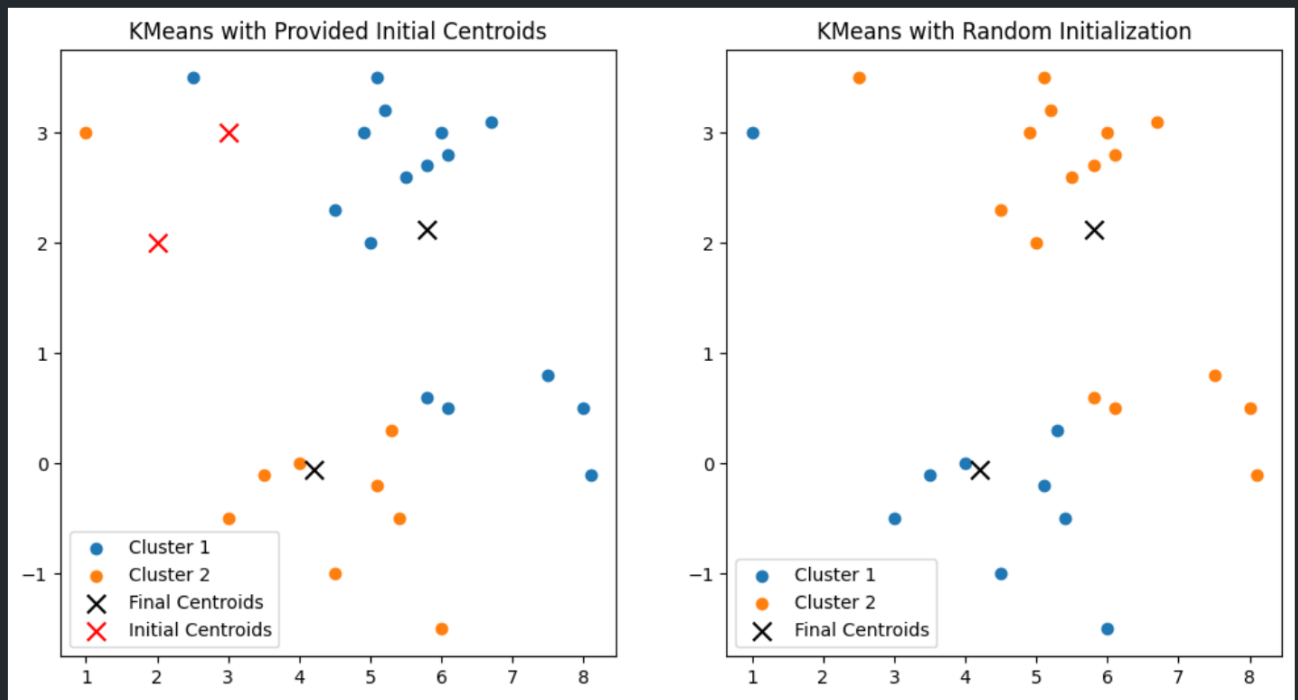

```
Final Centroids after convergence:  
[[ 5.8      2.125    ]  
 [ 4.2     -0.05555556]]
```

2. Final centroids



3. Provided initialization vs Random initialization of centroids

Convergence reached at iteration 3
Convergence reached at iteration 2



Final Centroids (Provided Initialization):

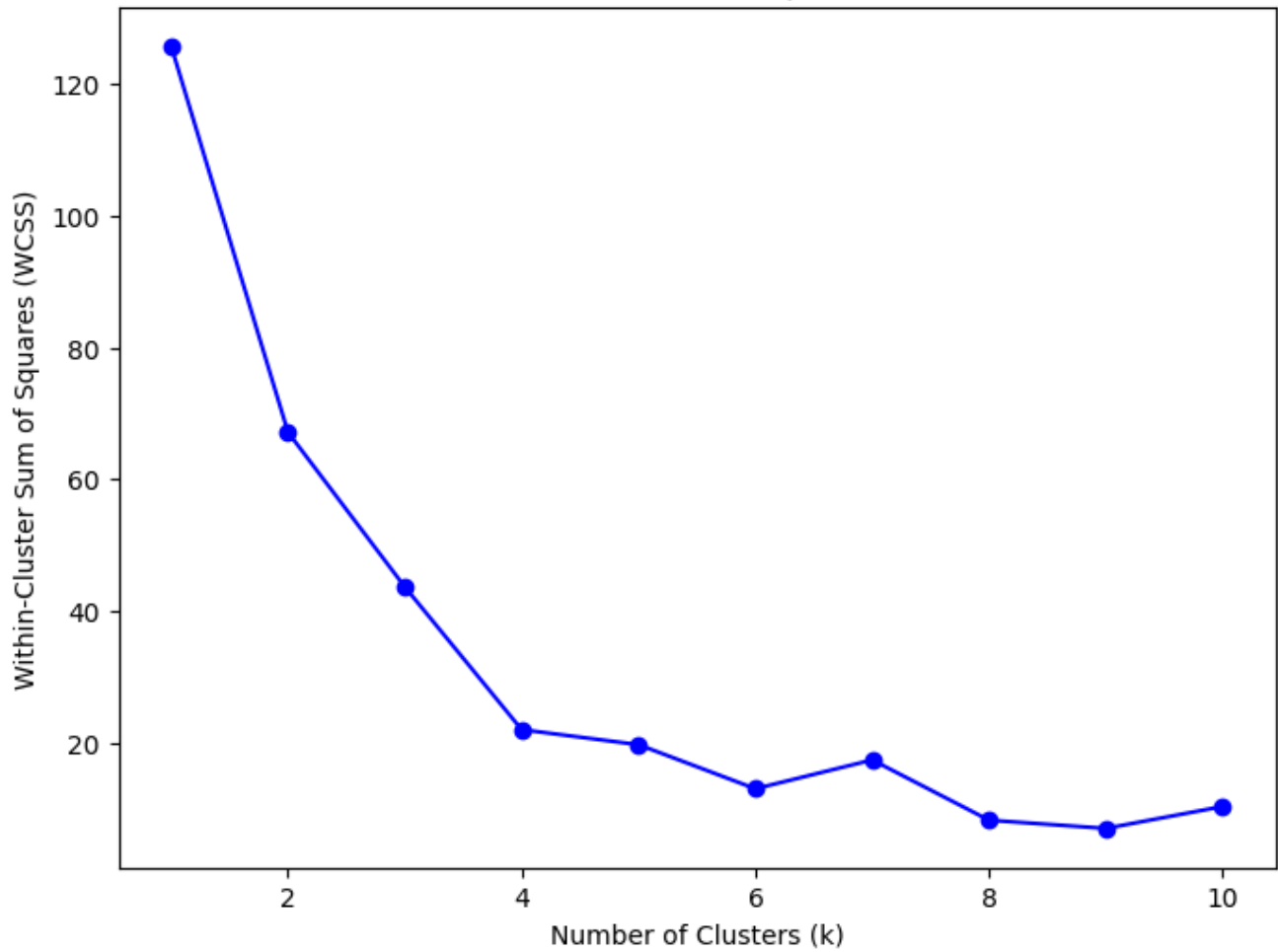
```
[[ 5.8      2.125      ]  
 [ 4.2     -0.05555556]]
```

Final Centroids (Random Initialization):

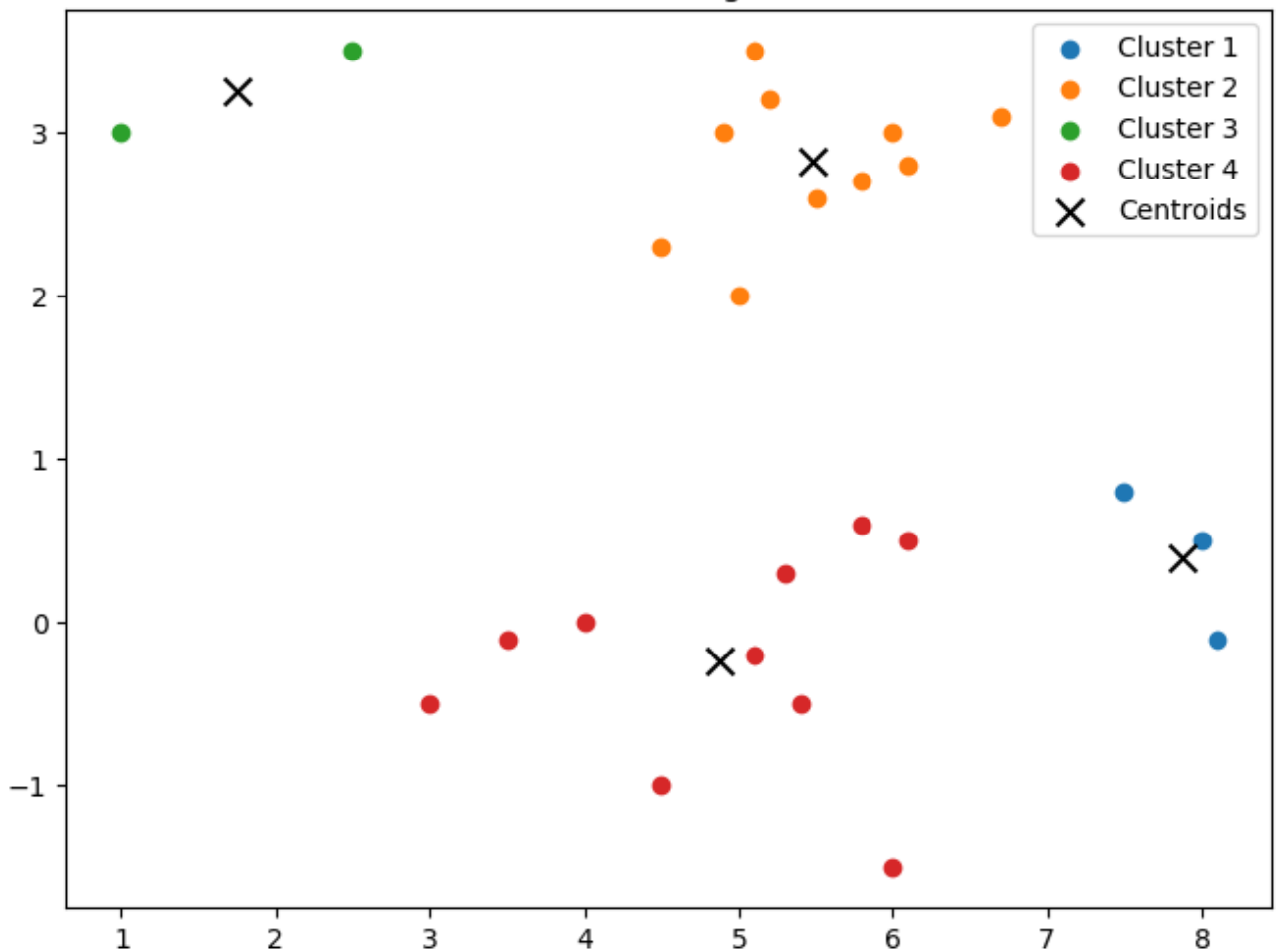
```
[[ 4.2     -0.05555556]  
 [ 5.8      2.125      ]]
```

4. The optimal number of clusters using the Elbow method.

Elbow Method for Optimal k



KMeans Clustering with k=4



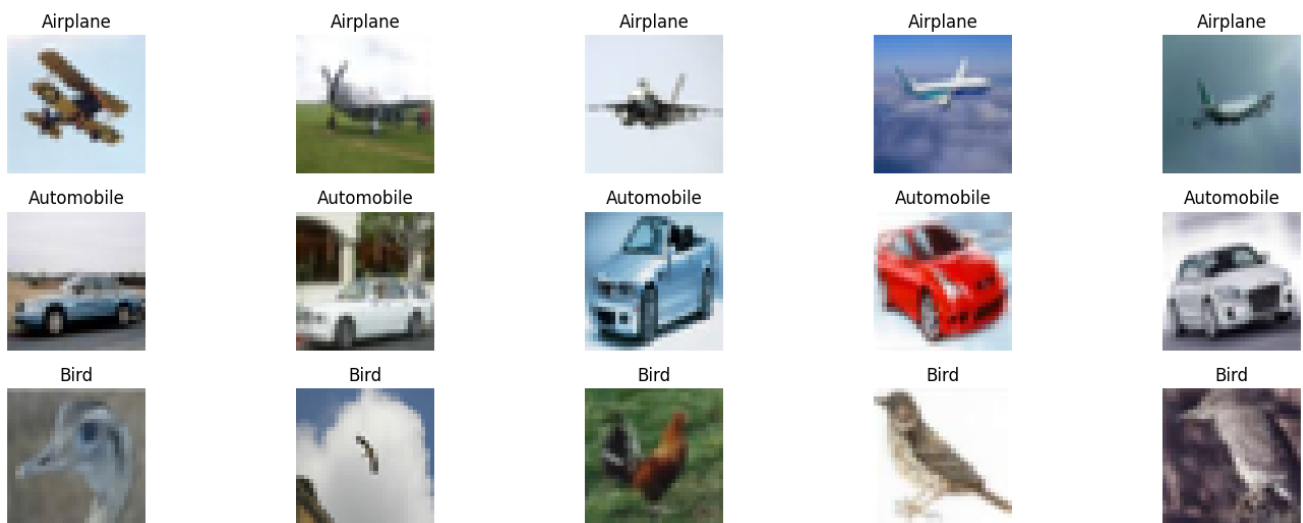
SECTION-C

1. Data Preparation

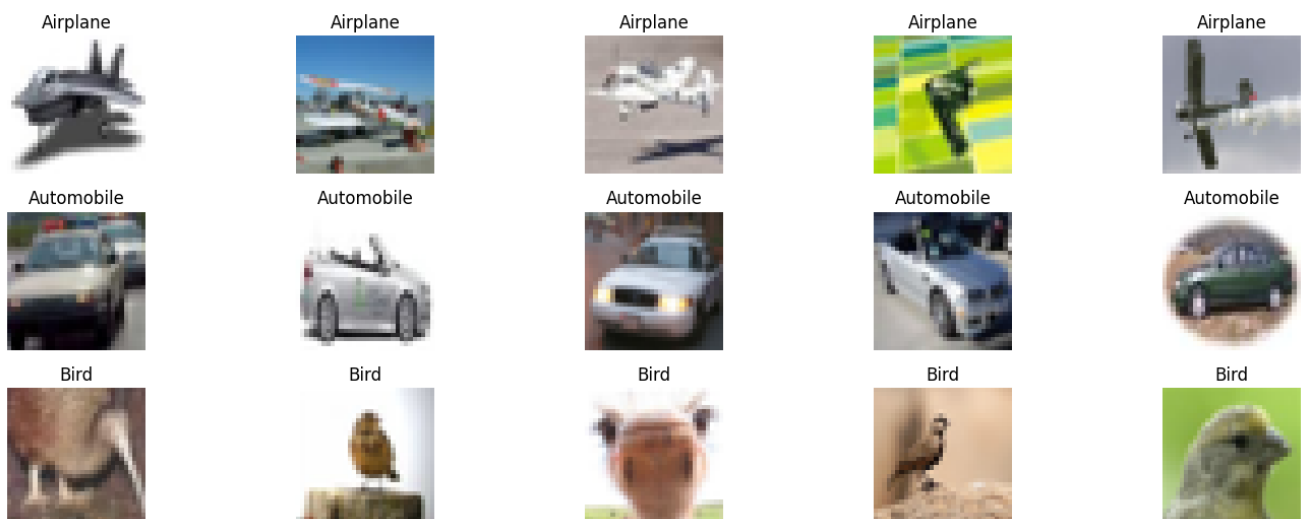
```
Files already downloaded and verified
Files already downloaded and verified
Train dataset size: 12000
Validation dataset size: 3000
Test dataset size: 3000
```

2. Visualization

Training Dataset



Validation Dataset

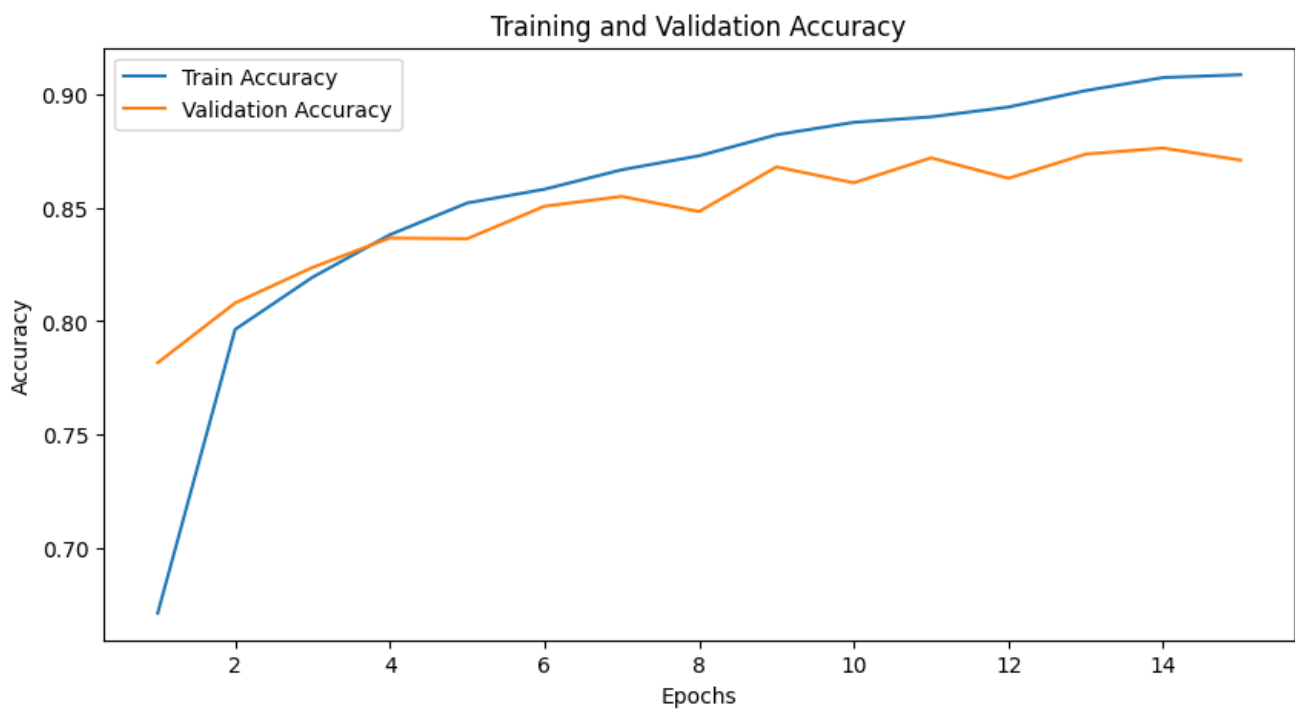
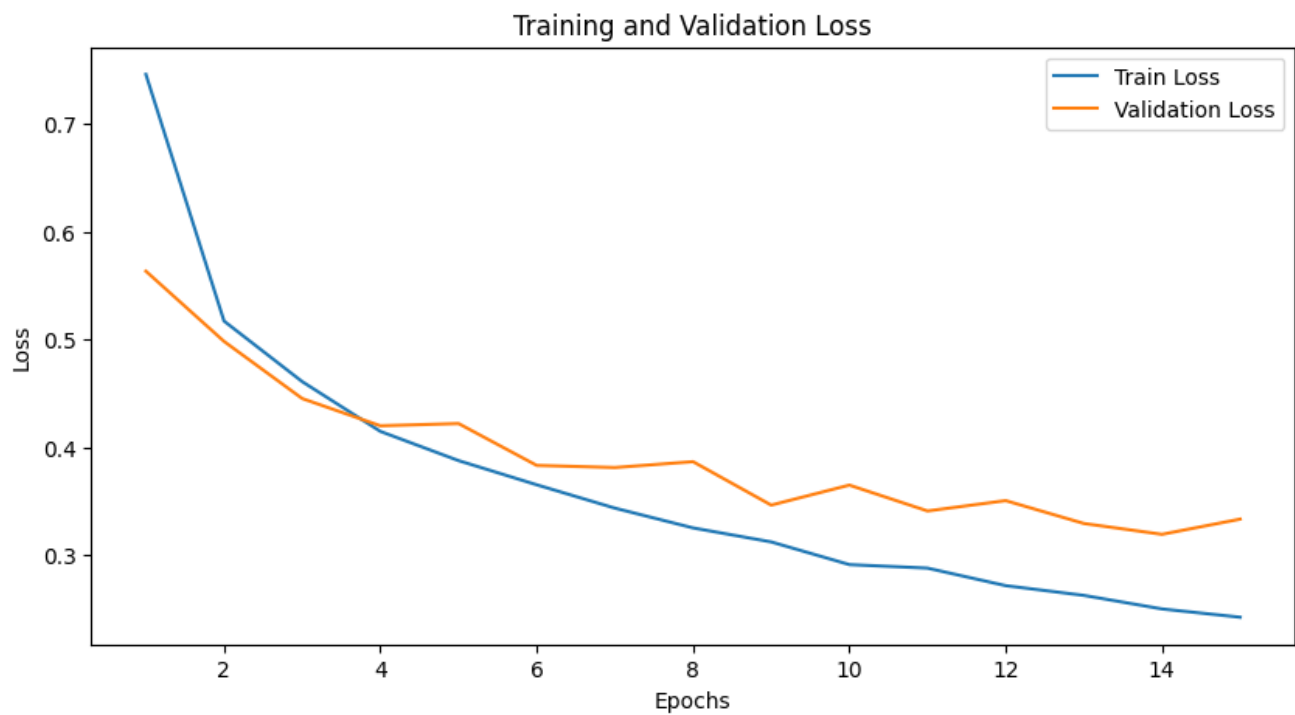


4. Training the model


```
Epoch 1/15
Train Loss: 0.7458, Train Accuracy: 0.6713, Val Loss: 0.5634, Val Accuracy: 0.7817
Best model saved at epoch 1
Epoch 2/15
Train Loss: 0.5171, Train Accuracy: 0.7963, Val Loss: 0.4982, Val Accuracy: 0.8080
Best model saved at epoch 2
Epoch 3/15
Train Loss: 0.4610, Train Accuracy: 0.8193, Val Loss: 0.4453, Val Accuracy: 0.8237
Best model saved at epoch 3
Epoch 4/15
Train Loss: 0.4148, Train Accuracy: 0.8381, Val Loss: 0.4200, Val Accuracy: 0.8367
Best model saved at epoch 4
Epoch 5/15
Train Loss: 0.3878, Train Accuracy: 0.8521, Val Loss: 0.4221, Val Accuracy: 0.8363
Epoch 6/15
Train Loss: 0.3653, Train Accuracy: 0.8582, Val Loss: 0.3833, Val Accuracy: 0.8507
Best model saved at epoch 6
Epoch 7/15
Train Loss: 0.3437, Train Accuracy: 0.8668, Val Loss: 0.3813, Val Accuracy: 0.8550
Best model saved at epoch 7
Epoch 8/15
Train Loss: 0.3254, Train Accuracy: 0.8729, Val Loss: 0.3868, Val Accuracy: 0.8483
Epoch 9/15
Train Loss: 0.3124, Train Accuracy: 0.8822, Val Loss: 0.3465, Val Accuracy: 0.8680
Best model saved at epoch 9
Epoch 10/15
Train Loss: 0.2914, Train Accuracy: 0.8877, Val Loss: 0.3651, Val Accuracy: 0.8610
Train Loss: 0.2881, Train Accuracy: 0.8901, Val Loss: 0.3411, Val Accuracy: 0.8720
Best model saved at epoch 11
Epoch 12/15
Train Loss: 0.2719, Train Accuracy: 0.8944, Val Loss: 0.3507, Val Accuracy: 0.8630
Epoch 13/15
Train Loss: 0.2628, Train Accuracy: 0.9017, Val Loss: 0.3295, Val Accuracy: 0.8737
Best model saved at epoch 13
Epoch 14/15
Train Loss: 0.2503, Train Accuracy: 0.9074, Val Loss: 0.3194, Val Accuracy: 0.8763
Best model saved at epoch 14
Epoch 15/15
Train Loss: 0.2426, Train Accuracy: 0.9087, Val Loss: 0.3335, Val Accuracy: 0.8710
Final model saved.
```

5. Testing

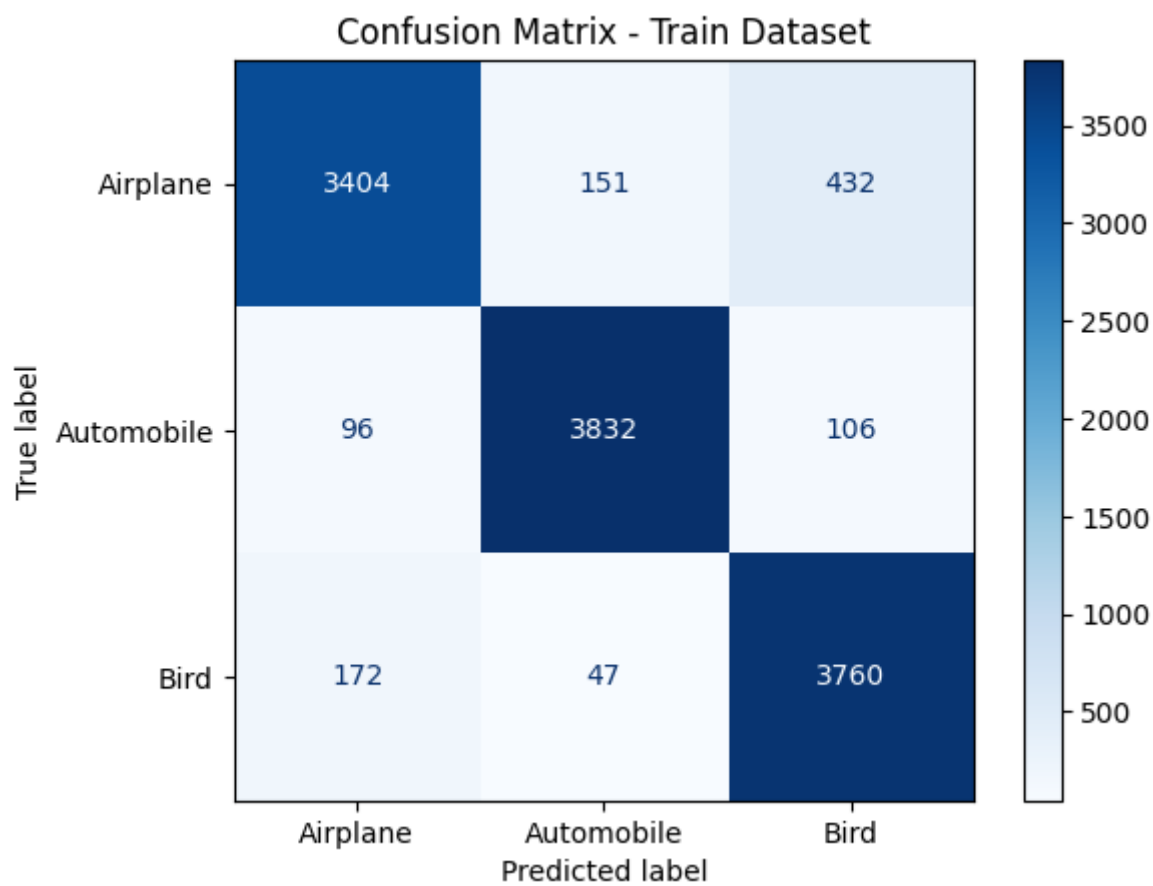
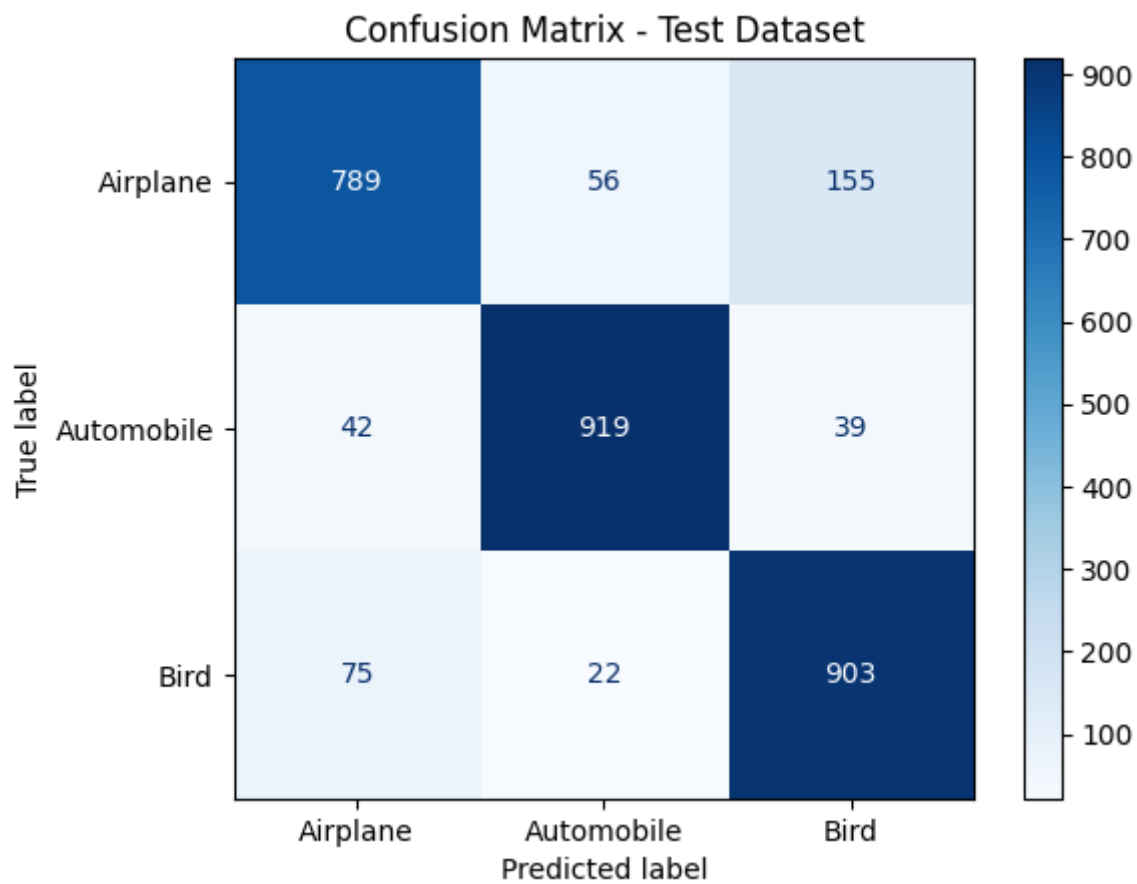
Plot Training and Validation Metrics

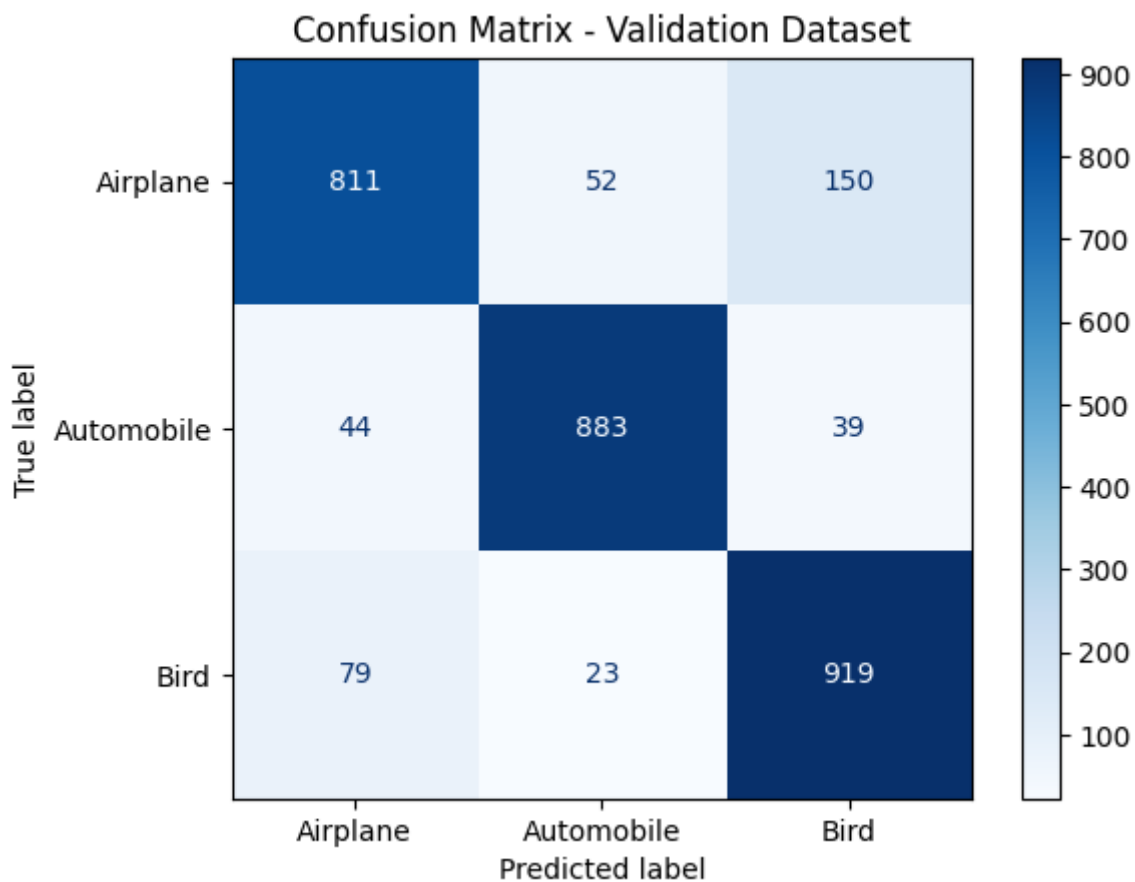


Evaluate Test Dataset Accuracy and F1-Score

```
Test Loss: 0.3294
Test Accuracy: 0.8703
Test F1-Score: 0.8698
```

Plot Confusion Matrices for Train, Val, and Test Datasets





6. Training an MLP

Define the MLP Model

```
Model Architecture:
MLPModel(
  (fc1): Linear(in_features=3072, out_features=64, bias=True)
  (relu): ReLU()
  (fc2): Linear(in_features=64, out_features=3, bias=True)
)
```

Training the MLP Model

```
Epoch 1/15
Train Loss: 0.6841, Train Accuracy: 0.7179, Val Loss: 0.6499, Val Accuracy: 0.7403
Best model saved at epoch 1
Epoch 2/15
Train Loss: 0.5649, Train Accuracy: 0.7773, Val Loss: 0.6175, Val Accuracy: 0.7600
Best model saved at epoch 2
Epoch 3/15
Train Loss: 0.5064, Train Accuracy: 0.8030, Val Loss: 0.5971, Val Accuracy: 0.7667
Best model saved at epoch 3
Epoch 4/15
Train Loss: 0.4601, Train Accuracy: 0.8175, Val Loss: 0.5864, Val Accuracy: 0.7670
Best model saved at epoch 4
Epoch 5/15
Train Loss: 0.4260, Train Accuracy: 0.8363, Val Loss: 0.5889, Val Accuracy: 0.7753
Epoch 6/15
Train Loss: 0.3907, Train Accuracy: 0.8531, Val Loss: 0.5818, Val Accuracy: 0.7740
Best model saved at epoch 6
Epoch 7/15
Train Loss: 0.3660, Train Accuracy: 0.8622, Val Loss: 0.6088, Val Accuracy: 0.7803
Epoch 8/15
Train Loss: 0.3417, Train Accuracy: 0.8728, Val Loss: 0.6088, Val Accuracy: 0.7767
Epoch 9/15
Train Loss: 0.3097, Train Accuracy: 0.8832, Val Loss: 0.6058, Val Accuracy: 0.7860
Epoch 10/15
Train Loss: 0.2992, Train Accuracy: 0.8866, Val Loss: 0.6569, Val Accuracy: 0.7787
Epoch 11/15
Train Loss: 0.2764, Train Accuracy: 0.9008, Val Loss: 0.6424, Val Accuracy: 0.7793
Epoch 12/15
Train Loss: 0.2509, Train Accuracy: 0.9085, Val Loss: 0.7072, Val Accuracy: 0.7670
Epoch 13/15
Train Loss: 0.2286, Train Accuracy: 0.9192, Val Loss: 0.6404, Val Accuracy: 0.7860
Epoch 14/15
Train Loss: 0.2047, Train Accuracy: 0.9277, Val Loss: 0.6920, Val Accuracy: 0.7743
Epoch 15/15
Train Loss: 0.1947, Train Accuracy: 0.9310, Val Loss: 0.7125, Val Accuracy: 0.7877
Final MLP model saved.
```

7. Infer and Compare

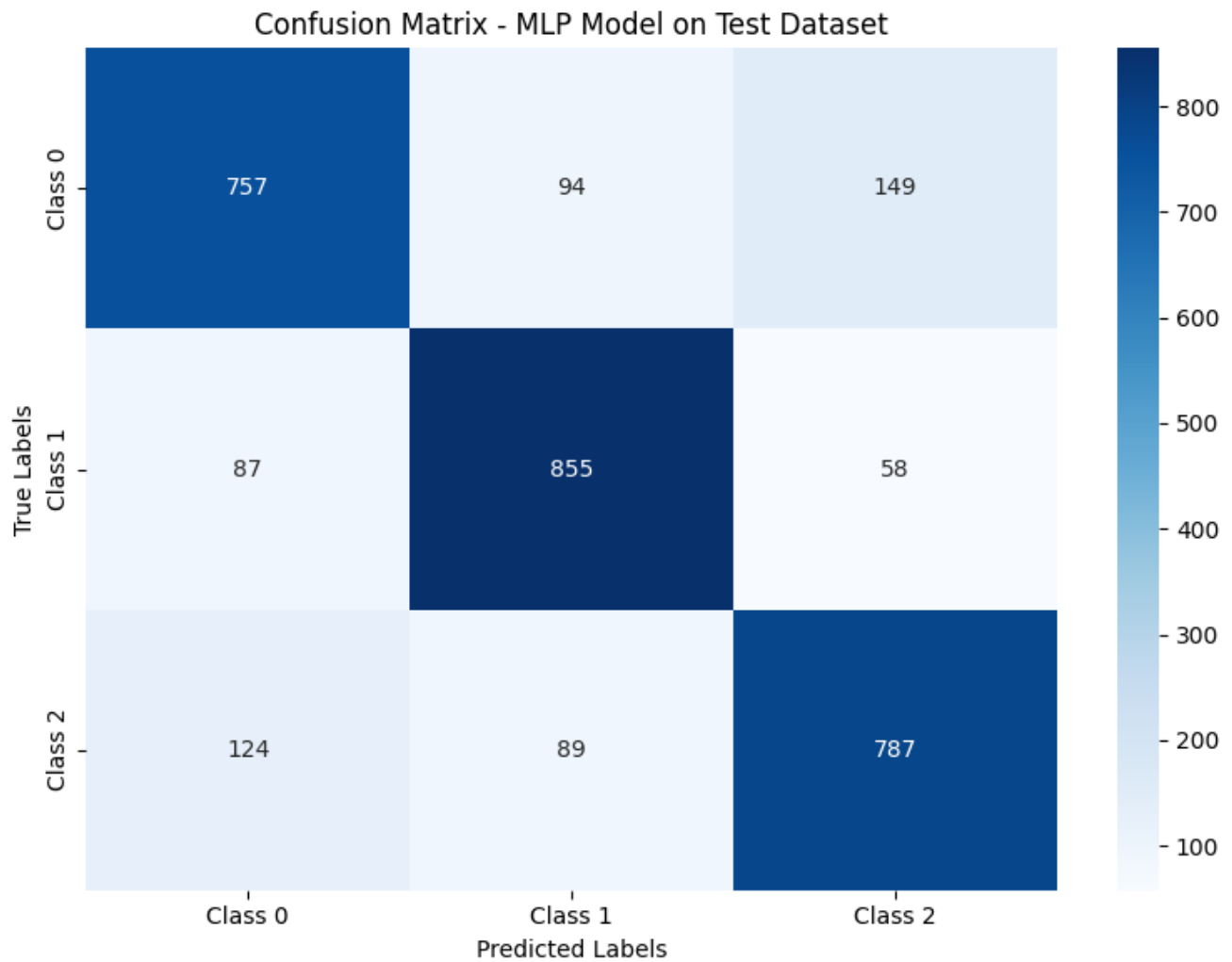
Evaluate MLP Model on Test Data

```
MLP Test Performance:
Loss: 0.5212, Accuracy: 0.7997, F1-Score: 0.7992
```

Plot Confusion Matrix for MLP Model

Confusion Matrix:

```
[[757  94 149]
 [ 87 855  58]
 [124  89 787]]
```



Compare Results with CNN

Model Performance Comparison:

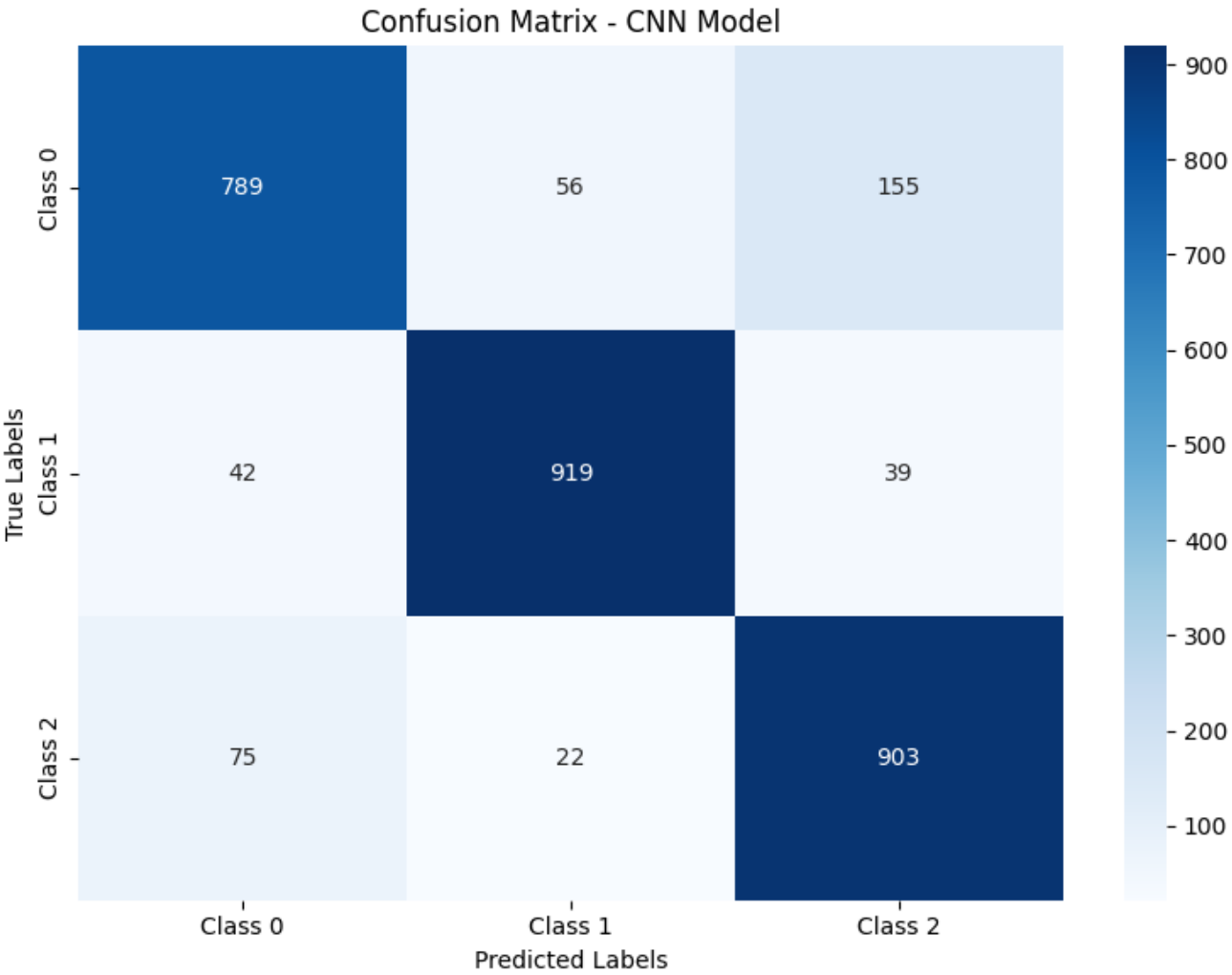
Metric	CNN		MLP	
Test Accuracy	0.8703		0.7997	
Test F1-Score	0.8698		0.7992	

Comparing Confusion Matrices:

CNN Model Confusion Matrix:

Confusion Matrix:

```
[[789  56 155]
 [ 42 919  39]
 [ 75  22 903]]
```



MLP Model Confusion Matrix:
Confusion Matrix:
[[757 94 149]
 [87 855 58]
[124 89 787]]

