

# Plots 2D

May 3, 2025

## 1 Importing Necessary Libraries

```
[1]: import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
import numpy as np
```

## 2 Loss and Accuracy Graph Plots

### 2.1 Loading the Model History DataFrame

```
[6]: hist_df = pd.read_csv("../History 2D.csv")
hist_df["epoch"] = hist_df.index + 1

accuracy_df = hist_df.melt(id_vars = "epoch", value_vars=["accuracy",
    ↪ "val_accuracy"], var_name="Dataset", value_name="Accuracy")
loss_df = hist_df.melt(id_vars = "epoch", value_vars = ["loss", "val_loss"],
    ↪ var_name = "Dataset", value_name= "Loss")
```

```
[10]: sns.set(style="whitegrid")

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Accuracy plot
sns.lineplot(data=accuracy_df, x="epoch", y="Accuracy", hue="Dataset",
    ↪ ax=axes[0])
axes[0].set_title("Training vs Validation Accuracy")
axes[0].set_xlabel("Epoch")
axes[0].set_ylabel("Accuracy")

# Loss plot
sns.lineplot(data=loss_df, x="epoch", y="Loss", hue="Dataset", ax=axes[1])
axes[1].set_title("Training vs Validation Loss")
axes[1].set_xlabel("Epoch")
```

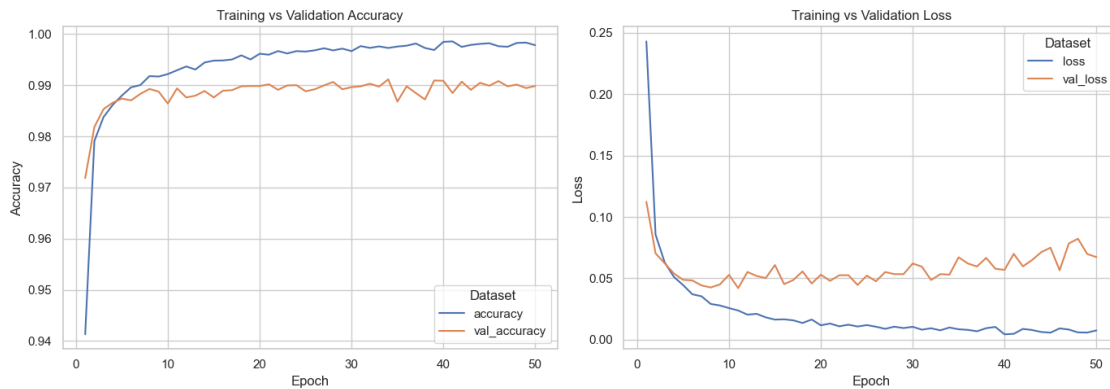
```

axes[1].set_ylabel("Loss")

plt.tight_layout()

plt.savefig("../Plots/2D/Combined Graphs 2D.png", dpi=300) # High-res PNG
plt.show()

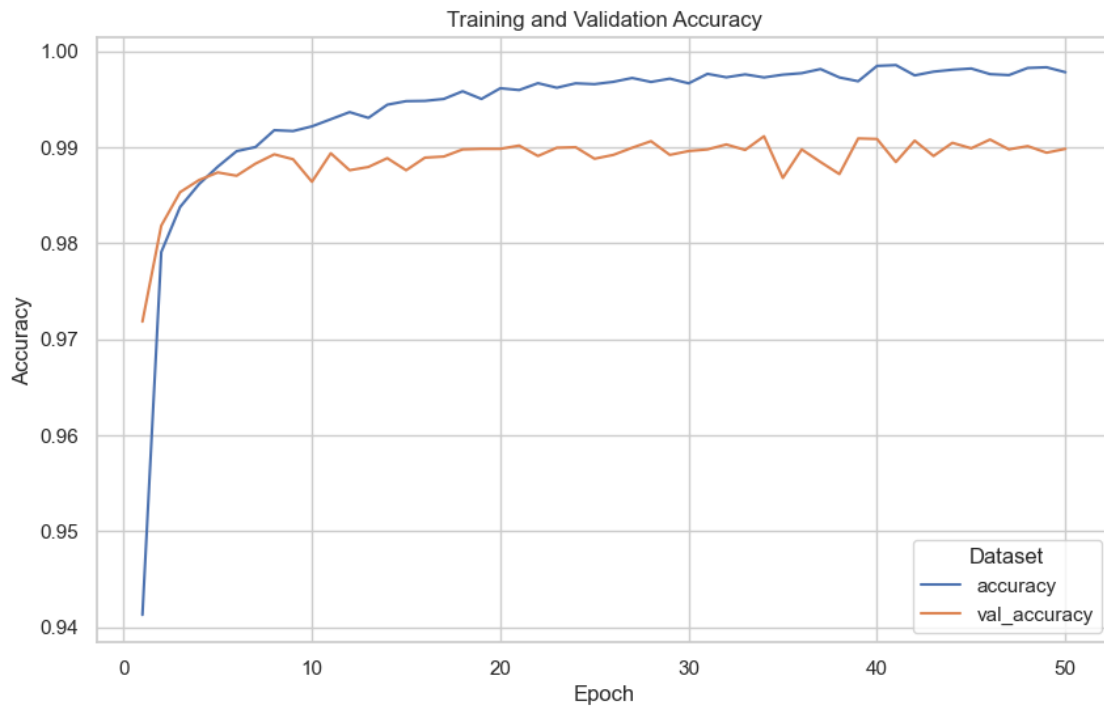
```



```

[12]: sns.set(style="whitegrid")
plt.figure(figsize=(10, 6))
sns.lineplot(data=accuracy_df, x="epoch", y="Accuracy", hue="Dataset")
plt.title("Training and Validation Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend(title="Dataset")
plt.savefig("../Plots/2D/Accuracy Graphs 2D.png", dpi=300) # High-res PNG
plt.show()

```



```
[14]: plt.figure(figsize=(10, 6))
sns.lineplot(data=loss_df, x="epoch", y="Loss", hue="Dataset")
plt.title("Training and Validation Loss")
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend(title="Dataset")
plt.savefig("../Plots/2D/Loss Graphs 2D.png", dpi=300)
plt.show()
```



### 3 Confusion Matrix

#### 3.1 Loading the Model and the Data

```
[18]: model = tf.keras.models.load_model("../Models/Model 2D.h5")
```

```
[24]: X = np.load("../Features.npy")
      y = np.load("../Labels (Mutli Class).npy")
```

#### 3.2 Splitting the Data and Performing Model Prediction

```
[27]: _, X_test, _, y_test = train_test_split(X, y, shuffle = True, random_state = 10, test_size = 0.2)
```

```
[29]: X_test.shape, y_test.shape
```

```
[29]: ((21884, 250, 2), (21884,))
```

```
[31]: y_pred_probs = model.predict(X_test)
      y_pred = y_pred_probs.argmax(axis = 1)
```

```
684/684 [=====] - 3s 2ms/step
```

```
[32]: y_true = y_test
```

### 3.2.1 Check for Missing Labels in y\_true and y\_pred

Carefully check the labels of both the True and the Predicted labels, then proceed to plotting the Confusion Matrix

```
[35]: values, _ = np.unique(y_true, return_counts = True)
```

```
[36]: values
```

```
[36]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13],  
        dtype=int64)
```

```
[37]: np.unique(y_true, return_counts = True)
```

```
[37]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13],  
        dtype=int64),  
      array([ 1352,   501,   21,   149,   22,  1620, 15135,  1411,    1,  
            1407,   28,    6,   191,   40], dtype=int64))
```

```
[38]: np.unique(y_pred, return_counts = True)
```

```
[38]: (array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13],  
        dtype=int64),  
      array([ 1351,   485,   21,   159,   20,  1616, 15148,  1416,    2,  
            1393,   35,    5,   191,   42], dtype=int64))
```

### 3.3 Plotting

```
[46]: cm = confusion_matrix(y_true, y_pred)
```

```
[48]: plt.figure(figsize = (8, 6))  
      sns.heatmap(cm, annot = True, fmt = "d", cmap = "Greens", cbar = False,  
                  xticklabels = values, yticklabels = values)  
      plt.xlabel("Predicted")  
      plt.ylabel("Actual")  
      plt.title("Confusion Matrix")  
      plt.tight_layout()  
  
      # Save the plot  
      plt.savefig("../Plots/2D/Confusion Matrix 2D.png", dpi=300)  
      plt.show()
```

		Confusion Matrix													
Actual	0	1350	0	0	0	0	0	1	0	0	0	0	0	1	0
	1	0	475	0	0	0	0	20	2	0	0	1	2	0	1
	2	0	0	21	0	0	0	0	0	0	0	0	0	0	0
	3	0	0	0	142	0	0	4	0	0	3	0	0	0	0
	4	0	0	0	0	20	0	0	2	0	0	0	0	0	0
	5	0	0	0	0	0	1615	5	0	0	0	0	0	0	0
	6	0	7	0	6	0	0	15103	0	1	6	6	0	1	5
	7	0	1	0	0	0	0	1	1409	0	0	0	0	0	0
	8	0	0	0	0	0	0	0	0	1	0	0	0	0	0
	9	1	0	0	11	0	1	7	3	0	1383	0	0	1	0
	10	0	0	0	0	0	0	0	0	0	0	28	0	0	0
	11	0	1	0	0	0	0	1	0	0	1	0	3	0	0
	12	0	0	0	0	0	0	3	0	0	0	0	0	188	0
	13	0	1	0	0	0	0	3	0	0	0	0	0	0	36
		0	1	2	3	4	5	6	7	8	9	10	11	12	13
		Predicted													

## 4 Classification Report

```
[53]: print(classification_report(y_true, y_pred))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1352
1	0.98	0.95	0.96	501
2	1.00	1.00	1.00	21
3	0.89	0.95	0.92	149
4	1.00	0.91	0.95	22
5	1.00	1.00	1.00	1620
6	1.00	1.00	1.00	15135
7	1.00	1.00	1.00	1411
8	0.50	1.00	0.67	1
9	0.99	0.98	0.99	1407
10	0.80	1.00	0.89	28
11	0.60	0.50	0.55	6
12	0.98	0.98	0.98	191
13	0.86	0.90	0.88	40

accuracy			0.99	21884
macro avg	0.90	0.94	0.91	21884
weighted avg	1.00	0.99	0.99	21884