```
In [1]:
          1 import pandas as pd
          2 import numpy as np
          3 from sklearn.model selection import train test split, GridSearchCV
          4 from sklearn.preprocessing import StandardScaler
          5 from sklearn.svm import SVC
          6 from sklearn.feature_selection import SelectKBest, f_classif
          7
             from sklearn.metrics import classification_report
             import matplotlib.pyplot as plt
             from sklearn.metrics import recall score, f1 score, confusion matrix
         10 from sklearn.metrics import accuracy_score, precision_score
             dataset_path = "D:/MTP/Mid Term/MId Term 256 models.csv"
In [2]:
            data = pd.read_csv(dataset_path)
          3 data.head()
Out[2]:
                                            Model
                                                   Model
                                                          Model
                                                                   natural
                                                                            natural
                                                                                      natura
            SI
                               y2
                                    area horizontal Vertical
                                                           Box frequency
                 x1 y1
                          х2
                                                                          frequency frequency
            No
                                            Class
                                                          Class
                                                                of Mode 1
                                                                                   of Mode 3
                                                    class
                                                                          of Mode 2
         0
             1 0.00 0.0 0.06 0.06 0.0036
                                                1
                                                       1
                                                              1
                                                                   6.8818
                                                                             25.361
                                                                                      27.925
         1
             2 0.06 0.0 0.12 0.06 0.0036
                                                1
                                                       1
                                                              1
                                                                   6.8854
                                                                             25.535
                                                                                      27.926
             3 0.12 0.0 0.18 0.06 0.0036
                                                                   6.9176
                                                                             25.713
                                                                                      27.932
                                                1
                                                       1
                                                              1
         3
             4 0.18 0.0 0.24 0.06 0.0036
                                                2
                                                       1
                                                              1
                                                                   6.9214
                                                                             25.759
                                                                                      27.926
             5 0.24 0.0 0.30 0.06 0.0036
                                                2
                                                              1
                                                       1
                                                                   6.9401
                                                                             25.767
                                                                                      27.916
In [3]:
             X = data.iloc[:, 9:] # Features: natural frequencies
             y horizontal = data['Model horizontal Class']
             y_vertical = data['Model Vertical class']
             y box = data['Model Box Class']
In [4]:
             def classify svm(X, y, label):
          1
          2
                 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
          3
                 scaler = StandardScaler()
          4
                 X_train_scaled = scaler.fit_transform(X_train)
          5
                 X test scaled = scaler.transform(X test)
          6
                 selector = SelectKBest(f classif, k='all')
          7
                 X train selected = selector.fit transform(X train scaled, y train)
          8
                 X test selected = selector.transform(X test scaled)
          9
                 param grid = {
         10
                      'C': [0.1, 1, 10],
                      'gamma': [0.1, 0.01, 0.001],
         11
                      'kernel': ['linear', 'rbf', 'poly']
         12
         13
         14
                 clf = GridSearchCV(SVC(), param_grid, cv=5)
         15
                 clf.fit(X_train_selected, y_train)
         16
                 y_train_pred = clf.predict(X_train_selected)
         17
                 y_test_pred = clf.predict(X_test_selected)
         18
                 return y_train, y_train_pred, y_test, y_test_pred
```

```
In [5]:
             1 train_actual_horizontal, train_predicted_horizontal, test_actual_horizonta
             2 train_actual_vertical, train_predicted_vertical, test_actual_vertical, test_actual_vertical.
             3 train_actual_box, train_predicted_box, test_actual_box, test_predicted_box
                train results df = pd.DataFrame({
In [6]:
             2
                      'Actual Horizontal Class': train_actual_horizontal,
             3
                      'Predicted Horizontal Class': train_predicted_horizontal,
             4
                      'Actual Vertical Class': train_actual_vertical,
             5
                      'Predicted Vertical Class': train_predicted_vertical,
                      'Actual Box Class': train actual box,
             6
                      'Predicted Box Class': train_predicted_box
             7
             8 })
             9
            10 test_results_df = pd.DataFrame({
                      'Actual Horizontal Class': test_actual_horizontal,
            11
                      'Predicted Horizontal Class': test_predicted_horizontal,
            12
                      'Actual Vertical Class': test_actual_vertical,
            13
            14
                      'Predicted Vertical Class': test_predicted_vertical,
                      'Actual Box Class': test_actual_box,
            15
                      'Predicted Box Class': test_predicted_box
            16
            17 })
In [7]:
             1 train_results_df['Horizontal Class Match'] = np.where(train_results_df['Ad
             2 train_results_df['Vertical Class Match'] = np.where(train_results_df['Actu
             3 train results_df['Box Class Match'] = np.where(train_results_df['Actual Bot
             4
             5 | test_results_df['Horizontal Class Match'] = np.where(test_results_df['Actu
                test_results_df['Vertical Class Match'] = np.where(test_results_df['Actual
                test_results_df['Box Class Match'] = np.where(test_results_df['Actual Box
             7
             8
                train_results_df['Cell Number'] = range(1, len(train_results_df) + 1)
            10
                test_results_df['Cell Number'] = range(len(train_results_df) + 1, len(trai
```

11

```
In [8]:
           1 # Counting 'Yes' and 'No' in training results
           2 train_yes_no_counts = {
                  'Horizontal Class Match': train_results_df['Horizontal Class Match'].√
           3
           4
                  'Vertical Class Match': train_results_df['Vertical Class Match'].value
                  'Box Class Match': train_results_df['Box Class Match'].value_counts()
           6 }
           7
           8 print("Training Results 'Yes' and 'No' Counts:")
          9 for key, value in train_yes_no_counts.items():
                  print(f"{key}:")
          10
                  print(f"Yes: {value['Yes']}, No: {value['No']}")
          11
          12
                 print()
         Training Results 'Yes' and 'No' Counts:
         Horizontal Class Match:
         Yes: 179, No: 25
         Vertical Class Match:
         Yes: 177, No: 27
         Box Class Match:
         Yes: 195, No: 9
In [9]:
           1 # Counting 'Yes' and 'No' in testing results
           2 test_yes_no_counts = {
                  'Horizontal Class Match': test_results_df['Horizontal Class Match'].va
           3
                  'Vertical Class Match': test results df['Vertical Class Match'].value
           4
                  'Box Class Match': test_results_df['Box Class Match'].value_counts()
           5
           6 }
           7
             print("\nTesting Results 'Yes' and 'No' Counts:")
          9 for key, value in test_yes_no_counts.items():
                 print(f"{key}:")
          10
                 print(f"Yes: {value['Yes']}, No: {value['No']}")
          11
          12
                 print()
          13
         Testing Results 'Yes' and 'No' Counts:
         Horizontal Class Match:
         Yes: 39, No: 13
         Vertical Class Match:
         Yes: 38, No: 14
         Box Class Match:
         Yes: 43, No: 9
In [10]:
           1 combined_results_df = pd.concat([train_results_df, test_results_df], ignor
```

```
def calculate_metrics_and_counts_df(actual, predicted):
In [11]:
                  report = classification_report(actual, predicted, output_dict=True)
           2
           3
                  counts = {'Yes': 0, 'No': 0}
           4
                  for key, value in report.items():
                      if key not in ['accuracy', 'macro avg', 'weighted avg']:
           5
                          counts['Yes'] += value['precision'] * value['support']
           6
           7
                          counts['No'] += (1 - value['precision']) * value['support']
                  metrics_df = pd.DataFrame(report).transpose()
           8
                  metrics_df = metrics_df[metrics_df.index.isin(['0', '1'])] # Consider
           9
                  counts_df = pd.DataFrame([counts], index=['Counts'])
          10
                  metrics_counts_df = pd.concat([metrics_df, counts_df])
          11
          12
                  return metrics_counts_df
```

In [12]: 1 # Calculate metrics for entire dataset accuracy_total_horizontal = accuracy_score(train_results_df['Actual Horizontal_score) precision_total_horizontal = precision_score(train_results_df['Actual Hori recall_total_horizontal = recall_score(train_results_df['Actual Horizontal 5 | f1_total_horizontal = f1_score(train_results_df['Actual Horizontal Class'] confusion_matrix_total_horizontal = confusion_matrix(train_results_df['Act 7 8 accuracy_total_vertical = accuracy_score(train_results_df['Actual Vertical precision_total_vertical = precision_score(train_results_df['Actual Vertical') 10 recall_total_vertical = recall_score(train_results_df['Actual Vertical Cla f1_total_vertical = f1_score(train_results_df['Actual Vertical Class'], tr confusion_matrix_total_vertical = confusion_matrix(train_results_df['Actual 12 13 14 | accuracy_total_box = accuracy_score(train_results_df['Actual Box Class'], 15 precision_total_box = precision_score(train_results_df['Actual Box Class'] 16 recall total box = recall score(train results df['Actual Box Class'], trai

17

f1_total_box = f1_score(train_results_df['Actual Box Class'], train_result

18 confusion_matrix_total_box = confusion_matrix(train_results_df['Actual Box

```
In [13]:
          1 # Print results for entire dataset - Horizontal Class
          2 print("Metrics for Entire Dataset - Horizontal Class:")
          3 print("Accuracy:", accuracy_total_horizontal)
          4 print("Precision:", precision_total_horizontal)
          5 print("Recall:", recall_total_horizontal)
          6 print("F1 Score:", f1_total_horizontal)
          7 print("Confusion Matrix:\n", confusion_matrix_total_horizontal)
          9 # Print results for entire dataset - Vertical Class
         10 print("\nMetrics for Entire Dataset - Vertical Class:")
         11 print("Accuracy:", accuracy_total_vertical)
         12 print("Precision:", precision_total_vertical)
         13 print("Recall:", recall_total_vertical)
         14 print("F1 Score:", f1_total_vertical)
         15 print("Confusion Matrix:\n", confusion_matrix_total_vertical)
         16
         17 # Print results for entire dataset - Box Class
         18 | print("\nMetrics for Entire Dataset - Box Class:")
         19 print("Accuracy:", accuracy_total_box)
         20 print("Precision:", precision_total_box)
         21 print("Recall:", recall_total_box)
         22 print("F1 Score:", f1_total_box)
         23 print("Confusion Matrix:\n", confusion_matrix_total_box)
        Metrics for Entire Dataset - Horizontal Class:
         Accuracy: 0.8774509803921569
         Precision: 0.8976060794688245
         Recall: 0.8774509803921569
         F1 Score: 0.8788953331408574
         Confusion Matrix:
         [[37 0 1 0 0]
         [11 26 1 0 0]
          [4 2 40 0 0]
          [2 0 3 39 0]
          [000137]]
        Metrics for Entire Dataset - Vertical Class:
         Accuracy: 0.8676470588235294
         Precision: 0.8976364052209754
         Recall: 0.8676470588235294
         F1 Score: 0.8710278005817745
         Confusion Matrix:
          [[30 1 1 1 2]
          [ 2 38 0 0 2]
          [0 0 48 0 7]
          [002249]
          [000037]]
        Metrics for Entire Dataset - Box Class:
         Accuracy: 0.9558823529411765
         Precision: 0.9610955493308435
         Recall: 0.9558823529411765
         F1 Score: 0.9565698934964224
         Confusion Matrix:
          [[18 0 0 0 0 0 0 0 0]
          [02000000000]
```

```
0 24
           0
              0
                 0
                     0
                        0
                           0]
        0 19
                     3
                        0
                           0]
                     0
     1
        0
           1 17
                  0
                        0
                           0]
 0
     0
        0
           0
              0 29
                    0
                        0
                           0]
0
     0
        0
           1
              0
                 0 21
                        0
                           0]
 0
     0
        0
           0
              0
                 0
                     3 18
                           0]
0 29]]
[ 0
           0
              0
                 0
                    0
```

In [14]:

```
1 # Calculate metrics for training data
   accuracy_train_horizontal = accuracy_score(train_results_df['Actual Horizontal')
   precision_train_horizontal = precision_score(train_results_df['Actual Hori
 3
  recall_train_horizontal = recall_score(train_results_df['Actual Horizontal
   f1_train_horizontal = f1_score(train_results_df['Actual Horizontal Class']
   confusion_matrix_train_horizontal = confusion_matrix(train_results_df['Act
 7
8
   accuracy train vertical = accuracy score(train results df['Actual Vertical
9
   precision_train_vertical = precision_score(train_results_df['Actual Vertical')
   recall_train_vertical = recall_score(train_results_df['Actual Vertical Cla
10
   f1_train_vertical = f1_score(train_results_df['Actual Vertical Class'], tr
11
12
   confusion_matrix_train_vertical = confusion_matrix(train_results_df['Actual
13
14
   accuracy train box = accuracy score(train results df['Actual Box Class'],
15
   precision_train_box = precision_score(train_results_df['Actual Box Class']
16
   recall_train_box = recall_score(train_results_df['Actual Box Class'], trai
17
   f1_train_box = f1_score(train_results_df['Actual Box Class'], train_result
18
   confusion_matrix_train_box = confusion_matrix(train_results_df['Actual Box
19
```

```
In [15]:
          1 # Print results for training data - Horizontal Class
          2 print("\nMetrics for Training Data - Horizontal Class:")
          3 print("Accuracy:", accuracy_train_horizontal)
          4 print("Precision:", precision_train_horizontal)
          5 print("Recall:", recall_train_horizontal)
          6 print("F1 Score:", f1_train_horizontal)
          7 print("Confusion Matrix:\n", confusion_matrix_train_horizontal)
          9 # Print results for training data - Vertical Class
         10 print("\nMetrics for Training Data - Vertical Class:")
         11 print("Accuracy:", accuracy_train_vertical)
         12 print("Precision:", precision_train_vertical)
         13 print("Recall:", recall_train_vertical)
         14 print("F1 Score:", f1_train_vertical)
         15 print("Confusion Matrix:\n", confusion_matrix_train_vertical)
         16
         17 # Print results for training data - Box Class
         18 | print("\nMetrics for Training Data - Box Class:")
         19 print("Accuracy:", accuracy_train_box)
         20 print("Precision:", precision_train_box)
         21 print("Recall:", recall_train_box)
         22 print("F1 Score:", f1_train_box)
         23 print("Confusion Matrix:\n", confusion_matrix_train_box)
         Metrics for Training Data - Horizontal Class:
         Accuracy: 0.8774509803921569
         Precision: 0.8976060794688245
         Recall: 0.8774509803921569
         F1 Score: 0.8788953331408574
         Confusion Matrix:
          [[37 0 1 0 0]
          [11 26 1 0 0]
          [4 2 40 0 0]
          [2 0 3 39 0]
          [000137]]
         Metrics for Training Data - Vertical Class:
         Accuracy: 0.8676470588235294
         Precision: 0.8976364052209754
         Recall: 0.8676470588235294
         F1 Score: 0.8710278005817745
         Confusion Matrix:
          [[30 1 1 1 2]
          [238 0 0 2]
          [ 0 0 48 0 7]
          [0 0 2 24 9]
          [ 0 0 0 0 37]]
         Metrics for Training Data - Box Class:
         Accuracy: 0.9558823529411765
         Precision: 0.9610955493308435
         Recall: 0.9558823529411765
         F1 Score: 0.9565698934964224
         Confusion Matrix:
```

[[18 0 0 0 0 0 0 0 0]

```
0 20
        0
           0
               0
                  0
                     0
                         0
                            0]
           0
                     0
                         0
                            0]
        0 19
                     3
               0
                  0
                         0
                            0]
 0
     1
        0
           1 17
                  0
                     0
                         0
                            0]
0
     0
        0
           0
               0 29
                     0
                         0
                            0]
0
     0
        0
           1
               0
                  0 21
                         0
                            0]
[ 0
     0
        0
           0
               0
                  0
                     3 18 0]
        0
           0
               0
                  0
                     0
                        0 29]]
```

In [16]:

```
1 # Calculate metrics for testing data
   accuracy_test_horizontal = accuracy_score(test_results_df['Actual Horizont
   precision test horizontal = precision score(test results df['Actual Horizontal
   recall_test_horizontal = recall_score(test_results_df['Actual Horizontal (
   f1_test_horizontal = f1_score(test_results_df['Actual Horizontal Class'],
   confusion matrix test horizontal = confusion matrix(test results df['Actual
7
   accuracy_test_vertical = accuracy_score(test_results_df['Actual Vertical (
8
9
   precision test vertical = precision score(test results df['Actual Vertical
10 | recall_test_vertical = recall_score(test_results_df['Actual Vertical Class
11
   f1_test_vertical = f1_score(test_results_df['Actual Vertical Class'], test
12
   confusion matrix test vertical = confusion matrix(test results df['Actual
13
14
   accuracy_test_box = accuracy_score(test_results_df['Actual Box Class'], te
15
   precision_test_box = precision_score(test_results_df['Actual Box Class'],
16
   recall_test_box = recall_score(test_results_df['Actual Box Class'], test_r
17
   f1_test_box = f1_score(test_results_df['Actual Box Class'], test_results_d
18
   confusion_matrix_test_box = confusion_matrix(test_results_df['Actual Box (
19
```

```
In [17]:
          1 # Print results for testing data - Horizontal Class
          2 print("\nMetrics for Testing Data - Horizontal Class:")
          3 print("Accuracy:", accuracy_test_horizontal)
          4 print("Precision:", precision_test_horizontal)
          5 print("Recall:", recall_test_horizontal)
          6 print("F1 Score:", f1_test_horizontal)
          7 print("Confusion Matrix:\n", confusion_matrix_test_horizontal)
          9 # Print results for testing data - Vertical Class
         10 print("\nMetrics for Testing Data - Vertical Class:")
         11 print("Accuracy:", accuracy_test_vertical)
         12 print("Precision:", precision_test_vertical)
         13 print("Recall:", recall_test_vertical)
         14 print("F1 Score:", f1_test_vertical)
         15 print("Confusion Matrix:\n", confusion_matrix_test_vertical)
         16
         17 # Print results for testing data - Box Class
         18 print("\nMetrics for Testing Data - Box Class:")
         19 print("Accuracy:", accuracy_test_box)
         20 print("Precision:", precision_test_box)
         21 print("Recall:", recall_test_box)
         22 print("F1 Score:", f1_test_box)
         23 print("Confusion Matrix:\n", confusion_matrix_test_box)
        Metrics for Testing Data - Horizontal Class:
         Accuracy: 0.75
         Precision: 0.8155906593406593
         Recall: 0.75
         F1 Score: 0.7551434990349019
         Confusion Matrix:
         [[ 9 0 1 0 0]
          [2 8 0 0 0]
          [4 2 11 1 0]
          [0 0 0 4 0]
         [10027]]
        Metrics for Testing Data - Vertical Class:
         Accuracy: 0.7307692307692307
         Precision: 0.8013157894736841
         Recall: 0.7307692307692307
         F1 Score: 0.7327421815408086
         Confusion Matrix:
          [[10 2 0 0 1]
         [0 3 1 0 2]
         [01701]
          [0 0 2 7 4]
```

Accuracy: 0.8269230769230769
Precision: 0.8774038461538461
Recall: 0.8269230769230769
F1 Score: 0.8370898332436794
Confusion Matrix:
[[4 0 0 3 0 0 0 0 0]

Metrics for Testing Data - Box Class:

[0000011]

8 print("Random 20 rows from the box_class_df DataFrame:")

Random 20 rows from the box_class_df DataFrame:

 $[0\ 5\ 0\ 0\ 0\ 0\ 0\ 0\ 0]$

9 random_20_rows

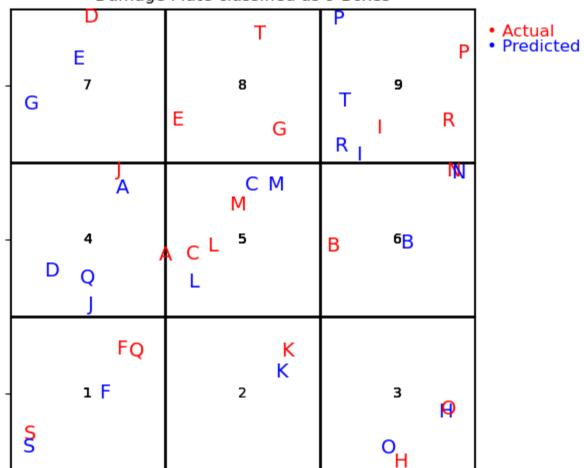
Out[18]:

	Actual Box Class	Predicted Box Class
106	6	6
58	2	2
112	2	2
0	6	6
140	9	9
150	7	7
55	4	7
13	4	7
148	8	8
82	6	6
218	5	5
223	2	2
226	5	5
12	7	7
125	8	8
34	6	6
175	9	9
157	1	1
100	8	8
41	3	3

```
In [31]:
           1 # Define the Damage Plate grid size
           2 plate_size = 3 # Adjusted for 20 alphabets
           4 # Create a 3x3 matrix to represent the Damage Plate grid
             Damage_Plate_grid = np.zeros((plate_size, plate_size), dtype=int)
           7 # Assign box numbers to each box in the grid
           8 \text{ box number} = 1
           9 for i in range(plate_size):
          10
                 for j in range(plate size):
          11
                     Damage_Plate_grid[i, j] = box_number
          12
                     box_number += 1
          13
          14 # Function to mark alphabets and write box numbers in the center
          15 def mark_alphabets(box_number_input, alphabet, color):
                 # Find the row and column indices of the box
          16
          17
                 for i in range(plate size):
          18
                     for j in range(plate_size):
          19
                          if Damage_Plate_grid[i, j] == box_number_input:
          20
                              row_index = i
          21
                              col_index = j
          22
          23
                 # Plot the alphabet randomly in the box
          24
                 rand_row = row_index + np.random.rand()
          25
                 rand_col = col_index + np.random.rand()
                 ax.text(rand_col, rand_row, alphabet, fontsize=14, ha='center', va='ce
          26
          27
          28
                 # Write the box number in the center
          29
                  ax.text(col_index + 0.5, row_index + 0.5, str(box_number_input), fonts
          30
          31 # Create the Damage_Plate grid plot
          32 fig, ax = plt.subplots(figsize=(6, 6))
          33
          34 # Plot the Damage Plate grid lines
          35 for i in range(plate size + 1):
                  ax.axhline(y=i, color='black', linewidth=2)
          36
          37
                  ax.axvline(x=i, color='black', linewidth=2)
          38
          39 # Get box numbers and corresponding values from your DataFrame (replace wi
          40 box1_numbers = box_class_df['Actual Box Class'].sample(n=20, random_state=
          41 box2_numbers = box_class_df['Predicted Box Class'].sample(n=20, random_sta
          42 | actual_values = [np.random.randint(1, 10) for _ in range(20)] # Replace w
          43
             predicted_values = [np.random.randint(1, 10) for _ in range(20)] # Replace
          44
          45 | alphabets = ['A', 'B', 'C', 'D', 'E', 'F', 'G', 'H', 'I', 'J', 'K', 'L',
          46 | color1 = 'red'
          47 color2 = 'blue'
          48
          49 # Mark alphabets and write box numbers
          50 for i in range(20):
          51
                 mark alphabets(box1 numbers[i], alphabets[i], color1)
          52
                 mark_alphabets(box2_numbers[i], alphabets[i], color2)
          53
          54 # Set plot limits and labels
          55 ax.set_xlim(0, plate_size)
```

```
56 ax.set_ylim(0, plate_size)
57 ax.set_xticks(np.arange(0.5, plate_size, 1))
58 ax.set_yticks(np.arange(0.5, plate_size, 1))
59 ax.set_xticklabels([])
60 ax.set_yticklabels([])
61 ax.grid(False)
62
63 # Create text labels outside the plot
64 offset x = 3.08 # Adjust x-offset for label placement
65 offset_y = 2.85 # Adjust y-offset for label placement
66
   label_text1 = plt.text(offset_x, offset_y, "\u2022 Actual", ha='left', va=
67
68 label_text2 = plt.text(offset_x, offset_y - 0.1, "\u2022 Predicted", ha=']
69
70 # Remove box around the labels (optional)
71 label_text1.set_bbox(dict(facecolor='none', edgecolor='none', pad=0))
72 label_text2.set_bbox(dict(facecolor='none', edgecolor='none', pad=0))
73
74 # Show the plot
75 plt.title('Damage Plate classified as 9 Boxes')
76 plt.show()
```

Damage Plate classified as 9 Boxes



Random 20 rows from the horizontal_class_df DataFrame:

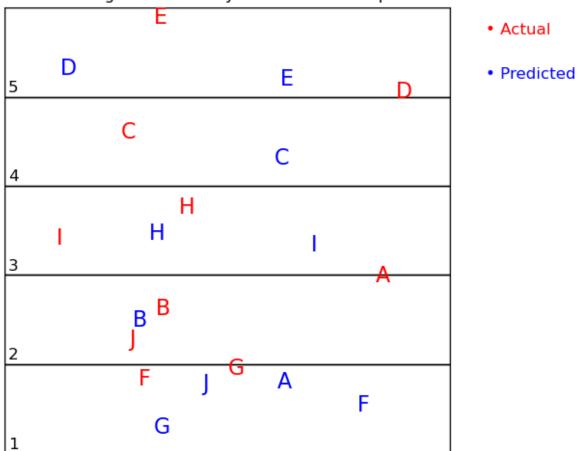
Out[20]:

	Actual Horizontal Class	Predicted Horizontal Class
91	2	1
188	2	2
137	4	4
207	5	5
237	5	5
130	1	1
90	1	1
62	3	3
133	3	3
25	2	1
253	3	2
224	4	4
32	3	3
194	3	3
86	4	4
53	1	1
125	3	1
94	5	5
112	3	3
7	4	4

```
In [41]:
          1 # Extract the actual and predicted horizontal class from the DataFrame
           2 actual_classes = random_20_rows_horizontal['Actual Horizontal Class'].toli
           3 predicted_classes = random_20_rows_horizontal['Predicted Horizontal Class'
           5 # Define the layout of the plate and strip labels
          6 strip_labels = ['5', '4', '3', '2', '1'] # Reverse order to label from bo
          7
          8 # Create a new figure
          9 fig, ax = plt.subplots(figsize=(8, 6))
          10
          11 # Plot horizontal strips and assign numbers
          12 for i, label in enumerate(strip_labels):
                 strip_y = (4 - i) / 5 # Adjusting the y-coordinate to represent bottom
          13
          14
                 rect_strip = plt.Rectangle((0, strip_y), 1, 1 / 5, fill=False, edgecol
          15
                 ax.add_patch(rect_strip)
                 # Add strip label at the left corner of each strip
          16
          17
                 ax.text(0.02, strip_y + 0.02, label, ha='center', va='center', fontsiz
          18
          19 # Set axis limits and labels
          20 ax.set_xlim(0, 1)
          21 ax.set_ylim(0, 1)
          22 ax.set_xticks([])
          23 ax.set yticks([])
          24 ax.set_aspect('equal')
          25
          26 # Add title
          27 plt.title('Damage Plate classify as Horizontal Strips')
          28
          29 # Initialize lists to store input data for red and blue alphabets
          30 red alphabets = []
          31 blue_alphabets = []
          32
          33 # Take 5 inputs for red alphabets
          34 for i, strip_num in enumerate(actual_classes):
          35
                 letter = chr(ord('A') + i) # Convert index to corresponding alphabet
          36
                 red_alphabets.append((letter, strip_num))
          37
          38 # Take 5 inputs for blue alphabets
          39 for i, strip_num in enumerate(predicted_classes):
          40
                 letter = chr(ord('A') + i) # Convert index to corresponding alphabet
          41
                 blue_alphabets.append((letter, strip_num))
          42
          43 # Function to mark alphabets on the plate
             def mark_alphabets(alphabets, color):
          45
                 for letter, strip_num in alphabets:
          46
                     if 1 <= strip_num <= 5:</pre>
                         strip_y = (strip_num - 1) / 5 # y-coordinate of the selected
          47
                         # Generate random x and y coordinates inside the selected stri
          48
          49
                         random_x_coordinate = np.random.uniform(0.1, 0.9) # Adjust th
                         random_y_coordinate = np.random.uniform(strip_y, strip_y + 0.2
          50
          51
                         # Marking the alphabet with specified color
                         ax.text(random_x_coordinate, random_y_coordinate, letter, ha='
          52
          53
          54 # Create text labels outside the plot
          55 offset_x = 1.08 # Adjust x-offset for label placement
```

```
offset_y = .95 # Adjust y-offset for label placement
57
1 label_text1 = plt.text(offset_x, offset_y, "\u2022 Actual", ha='left', va=
   label_text2 = plt.text(offset_x, offset_y - 0.1, "\u2022 Predicted", ha=']
59
60
61 # Mark red alphabets
   mark_alphabets(red_alphabets, 'red')
63
64 # Mark blue alphabets
65 mark_alphabets(blue_alphabets, 'blue')
66
67 # Show the plot
   plt.show()
68
69
```

Damage Plate classify as Horizontal Strips



```
In [22]: 1 # Selecting actual and predicted classes for the vertical class
vertical_class_df = combined_results_df[['Actual Vertical Class', 'Predict'

# Select 20 random rows for demonstration
random_20_rows_vertical = vertical_class_df.sample(n=20)

print("Random 20 rows from the vertical_class_df DataFrame:")
random_20_rows_vertical
```

Random 20 rows from the vertical_class_df DataFrame:

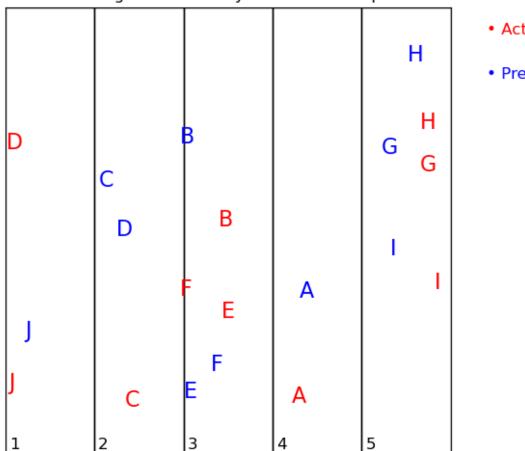
Out[22]:

	Actual Vertical Class	Predicted Vertical Class
9	4	4
203	3	3
57	2	2
225	1	2
186	3	3
177	3	3
125	5	5
132	5	5
127	5	5
133	1	1
210	5	5
27	1	1
158	5	5
250	1	1
148	4	4
147	1	1
229	3	3
55	3	5
51	5	5
54	2	2

```
In [44]:
           1 # Extract the actual and predicted vertical class from the DataFrame
           2 actual_classes = random_20_rows_vertical['Actual Vertical Class'].tolist()
           3 predicted_classes = random_20_rows_vertical['Predicted Vertical Class'].td
           5 # Define the layout of the plate and strip labels
           6 strip_labels = ['1', '2', '3', '4', '5'] # Label from bottom to top for ν
           7
           8 # Create a new figure
          9 fig, ax = plt.subplots(figsize=(8, 6))
          10
          11 # Plot vertical strips and assign numbers
          12 for i, label in enumerate(strip_labels):
                 strip x = i / 5 # Adjusting the x-coordinate to represent leftmost st
          13
          14
                 rect_strip = plt.Rectangle((strip_x, 0), 1 / 5, 1, fill=False, edgecol
          15
                 ax.add_patch(rect_strip)
                 # Add strip label at the bottom corner of each strip
          16
          17
                 ax.text(strip_x + 0.02, 0.02, label, ha='center', va='center', fontsiz
          18
          19 # Set axis limits and labels
          20 ax.set_xlim(0, 1)
          21 ax.set_ylim(0, 1)
          22 ax.set_xticks([])
          23 ax.set yticks([])
          24 ax.set_aspect('equal')
          25
          26 # Add title
          27 plt.title('Damage Plate classify as Vertical Strips')
          28
          29 # Initialize lists to store input data for red and blue alphabets
          30 red alphabets = []
          31 blue_alphabets = []
          32
          33 # Take 5 inputs for red alphabets
          34 for i, strip_num in enumerate(actual_classes):
          35
                  letter = chr(ord('A') + i) # Convert index to corresponding alphabet
          36
                 red_alphabets.append((letter, strip_num))
          37
          38 # Take 5 inputs for blue alphabets
          39 | for i, strip_num in enumerate(predicted_classes):
          40
                  letter = chr(ord('A') + i) # Convert index to corresponding alphabet
          41
                 blue_alphabets.append((letter, strip_num))
          42
          43 # Function to mark alphabets on the plate
             def mark_alphabets(alphabets, color):
          45
                 for letter, strip_num in alphabets:
          46
                     if 1 <= strip_num <= 5:</pre>
                          strip_x = (strip_num - 1) / 5 # x-coordinate of the selected
          47
                         # Generate random x and y coordinates inside the selected stri
          48
          49
                         random_x_coordinate = np.random.uniform(strip_x, strip_x + 0.2
                          random_y_coordinate = np.random.uniform(0.1, 0.9) # Adjust th
          50
          51
                          # Marking the alphabet with specified color
                          ax.text(random_x_coordinate, random_y_coordinate, letter, ha='
          52
          53
          54 # Create text labels outside the plot
          55 offset_x = 1.08 # Adjust x-offset for label placement
```

```
56 offset_y = .95 # Adjust y-offset for label placement
57
1 label_text1 = plt.text(offset_x, offset_y, "\u2022 Actual", ha='left', va=
   label_text2 = plt.text(offset_x, offset_y - 0.1, "\u2022 Predicted", ha=']
59
60
61 # Mark red alphabets
   mark_alphabets(red_alphabets, 'red')
63
64 # Mark blue alphabets
65 mark_alphabets(blue_alphabets, 'blue')
66
67 # Show the plot
   plt.show()
68
69
```

Damage Plate classify as Vertical Strips



- Actual
- Predicted