Neural Networks and Deep Learning

Feedforward Neural Networks

Natalia Wojarnik

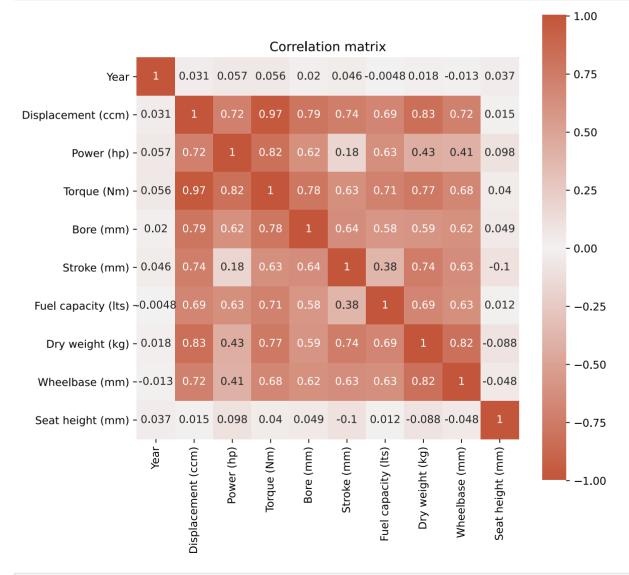
Motorcycle Category Prediction Based on Specifications

```
In [ ]: from functions import *
                import pandas as pd #Python Data Analysis Library
                import numpy as np #Python Scientific Library
                #scikit for machine Learning reporting
                from sklearn.metrics import mean_squared_error
                from sklearn.metrics import classification_report
                from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
                from sklearn.metrics import accuracy_score
                from sklearn.model_selection import train_test_split
                from sklearn.neural_network import MLPClassifier
                import matplotlib.pyplot as plt
                import seaborn as sns
In [ ]: url_cat = 'https://raw.githubusercontent.com/rsc22/Motocrcycle_Classification/main/results/preprocessed cat df.c
                url_num = 'https://raw.githubusercontent.com/rsc22/Motocrcycle_Classification/main/results/preprocessed_num_df.
                df_cat = pd.read_csv(url_cat, index_col=0)
                df_num_feat = pd.read_csv(url_num, index_col=0)
                data_labels = df_cat.loc[:,'Category']
                unique_labels = data_labels.unique()
                # Preparing arrays for model initilization
                num_labels_dict = {k:v for (k,v) in zip(range(len(unique_labels)), unique_labels)} # Keys are numbers, values an
                labels_num\_dict = \{v: k for (k,v) in num\_labels\_dict.items()\} # Keys are labels, values are the corresponding number of the corresponding nu
                numeric_labels = data_labels.apply(lambda x: labels_num_dict[x]) # Identify each Label with a number
                binary_labels, names = binarize_categorical(data_labels) # binary_labels is a matrix of size n_rows*n_categories
                df_cat_feat = df_cat.loc[:,[c for c in df_cat.columns if c!='Category']]
                df_cat_std = StandardScaler().fit(df_cat_feat).transform(df_cat_feat)
               df_cat_feat.loc[:,:] = df_cat_std
                df cat feat.sort index(inplace=True)
                df_feats = pd.concat([df_num_feat, df_cat_feat], axis = 1)
                df_cat_feat.sort_index(inplace=True)
                df num feat.sort index(inplace=True)
                df_feats = pd.concat([df_num_feat, df_cat_feat], axis = 1)
               print ("Data to learn (x): ",df_feats.shape)
                print ("Gold labels (y): ",data_labels.shape)
                #Using one hot encoding
                labels=pd.get_dummies(data_labels)
                labels.sample(5)
                # Sorting data labels names for comfusion matrix display
                label names=data labels.unique().tolist()
                label_names.sort()
               Data to learn (x): (2322, 43)
               Gold labels (y): (2322,)
In [ ]: features = list(df_feats.columns.values)
                print('-----
                print(f'The model uses {len(features)} features:\n')
                for x in features:
                      print(x + '\n')
```

```
The model uses 43 features:
Year
Displacement (ccm)
Power (hp)
Torque (Nm)
Bore (mm)
Stroke (mm)
Fuel capacity (lts)
Dry weight (kg)
Wheelbase (mm)
Seat height (mm)
n_cylinders
Engine stroke_ four-stroke
Fuel system_reduced_0
Fuel control_Other
Cooling system_Liquid
Cooling system_Air
Cooling system_Oil & air
Transmission type_Chain
Transmission type_Belt
Transmission type_Shaft drive
n_disks_front
abs
has_front_disk
n_pistons_front
n_disks_rear
has_rear_disk
n_pistons_rear
Rear tire_width
Rear tire_height
Rear tire_diameter
Front tire_width
Front tire_height
Front tire_diameter
reartyre_speed
fronttyre_speed
```

Rear tire_construction_B

```
Front tire_construction_B
Rear tire_label_format_I
Rear tire_label_format_N
Rear tire_label_format_A
Front tire_label_format_I
Front tire_label_format_N
Front tire_label_format_A
```



```
In [ ]: corr_matrix = df_cat_feat.corr()
my_cmap = sns.diverging_palette(20, 20, as_cmap=True)
fig, ax = plt.subplots(figsize=(30,30))
```

Out[]: Text(0.5, 1.0, 'Correlation matrix')

```
n_cylinders - 1 0.067 0.29 -0.25 0.24 -0.31 0.077 0.021 -0.27 0.32 0.53 0.25 0.17 0.31 0.32
                                                                                                               0.19 0.54 0.3 0.19 0.36 0.15 0.13 0.46 0.46 -0.47 -0.45 0.13 -0.14 -0.0032 0.14 -0.14 -0.0037
Engine stroke_four-stroke - 0.067 1 0.14 -0.028 0.085 -0.029 -0.091 0.073 -0.0041 -0.1 0.063 0.071 0.073 0.07 0.089
                                                                                                               0.051 0.098 0.096 0.048 0.074 0.062 0.036 0.069 0.068 -0.05 -0.046 0.14 -0.15 0.009 0.13 -0.14 0.011
 Fuel system_reduced_0 - 0.29 0.14 1 -0.35 0.27 -0.32 0.058 -0.09 0.04 0.079 0.43 0.41 0.22 0.29 0.44
                                                                                                               0.16 0.44 0.24 -0.02 0.39 0.21 -0.04 0.25 0.24 -0.35 -0.33 0.33 -0.35 0.017 0.32 -0.35 0.025
     Fuel control_Other - -0.25 -0.028 -0.35 1 -0.3 0.36 -0.056 -0.078 0.041 0.06 -0.31 -0.26 -0.21 -0.17 -0.26
                                                                                                               -0.074 -0.25 -0.18 -0.0029 -0.23 -0.12 -0.0074 -0.11 -0.11 0.23 0.21 -0.24 0.25 0.0099 -0.24 0.26 6.1e-05
  Cooling system_Liquid - 0.24 0.085 0.27 -0.3 1 -0.78 -0.42 0.17 -0.21 0.017 0.3 0.19 0.16 0.031 0.31
                                                     -0.24 -0.096 0.17 -0.079 -0.45 -0.23 -0.21 -0.18 -0.41
                                                                                                                -0.077 -0.38 -0.23 -0.095 -0.28 -0.087 -0.089 -0.2 -0.19 0.26 0.27 -0.28 0.26 0.1 -0.3 0.28 0.12
Cooling system_Oil & air - 0.077 -0.091 0.058 -0.056 -0.42 -0.24 1 -0.13 0.076 0.088 0.18 0.032 0.056 0.21 0.12
                                                                                                                0.34 0.18 0.1 0.05 0.17 0.053 0.048 0.029 0.029 0.0082 0.035 0.068 0.063 0.025 0.073 0.067 0.029
Transmission type_Chain - 0.021 0.073 -0.09 -0.078 0.17 -0.096 -0.13 1 -0.74 -0.5 0.038 -0.059 0.033 -0.056 0.094
                                                                                                                -0.2 -0.042 -0.1 0.23 -0.23 -0.28 0.16 0.21 0.2 -0.074 -0.043 0.005 0.027 -0.09 0.0097 0.032 -0.11
 Transmission type_Belt - 0.27 -0.0041 0.04 0.041 -0.21 0.17 0.076 -0.74 1 -0.22 -0.2 0.037 -0.09 0.03 -0.16
                                                                                                                0.19 -0.092 -0.019 -0.32 0.14 0.17 -0.26 -0.28 -0.28 0.2 0.19 -0.057 0.017 0.12 -0.063 0.0098 0.14
 0.033 0.18 0.17 0.073 0.16 0.19 0.1 0.06 0.066 -0.16 -0.18 0.067 -0.061 -0.026 0.067 -0.059 -0.031
        n_disks_front- 0.53 0.063 0.43 0.31 0.3 0.45 0.18 0.038 0.2 0.2 1 0.33 0.5 0.35 0.51
                                                                                                                0.26 0.63 0.3 0.22 0.49 0.15 0.16 0.39 0.38 -0.44 0.45 0.26 -0.26 -0.057 0.26 -0.26 -0.041
               abs - 0.25 0.071 0.41 -0.26 0.19 -0.23 0.032 -0.059 0.037 0.037 0.33 1 0.16 0.42 0.32
                                                                                                                0.29 0.35 0.22 0.08 0.31 0.18 0.081 0.12 0.12 -0.29 -0.24 0.14 -0.16 0.051 0.13 -0.17 0.068
       has_front_disk - 0.17 0.073 0.22 -0.21 0.16 -0.21 0.056 0.033 -0.09 0.068 0.5 0.16 1 0.16 0.42
                                                                                                                0.11 0.31 0.26 0.17 0.26 0.12 0.15 0.11 0.11 -0.16 -0.15 0.22 -0.24 0.012 0.21 -0.23 0.014
       n_pistons_front - 0.31 0.07 0.29 -0.17 0.031 -0.18 0.21 -0.056 0.03 0.043 0.35 0.42 0.16 1 0.3
                                                                                                                 .61 0.51 0.23 0.13 0.4 0.2 0.089 0.17 0.16 -0.23 -0.22 0.12 -0.15 0.07 0.12 -0.16 0.086
         n_disks_rear - 0.32  0.089  0.44  -0.26  0.31  -0.41  0.12  0.094  -0.16  0.076  0.51  0.32  0.42  0.3
                                                                                                                0.22 0.52 0.36 0.24 0.42 0.21 0.22 0.25 0.24 -0.33 -0.31 0.31 -0.33 0.025 0.3 -0.33 0.029
        has_rear_disk
       n_pistons_rear - 0.19 0.051 0.16 -0.074 -0.15 -0.077 0.34 -0.2 0.19 0.033 0.26 0.29 0.11 0.61 0.22
                                                                                                                1 0.4 0.23 0.084 0.34 0.23 0.074 0.051 0.051 -0.045 -0.059 0.071 -0.094 0.049 0.071 -0.11 0.075
                     0.54 0.098 0.44 -0.25 0.24 -0.38 0.18 -0.042 -0.092 0.18 0.63 0.35 0.31 0.51 0.52
                                                                                                                      1 0.53 0.18 0.76 0.41 0.11 0.39 0.39 -0.48 -0.47 0.36 -0.36 -0.37 0.36 -0.38 -0.015
       Rear tire_height - 0.3 0.096 0.24 -0.18 0.15 -0.23 0.1 -0.1 -0.019 0.17 0.3 0.22 0.26 0.23 0.36
                                                                                                                0.23 0.53 1 0.084 0.51 0.69 0.17 0.038 0.039 0.12 0.096 0.47 0.53 0.089 0.42 0.49 0.11
                                                                                                                0.084 0.18 0.084 1 0.0059 0.068 0.76 0.11 0.11 0.13 0.12 0.04 0.038 0.012 0.019 0.013 0.017
     Rear tire_diameter - 0.19  0.048  0.02  0.0029  0.057  0.095  0.05  0.23  0.32  0.073  0.22  0.08  0.17  0.13  0.24
      Front tire, width - 0.36 0.074 0.39 0.23 0.15 0.28 0.17 0.23 0.14 0.16 0.49 0.31 0.26 0.4 0.42
                                                                                                                0.34 0.76 0.51 0.0059 1 0.67 -0.13 0.27 0.27 -0.36 -0.39 0.35 -0.39 0.047 0.37 -0.43 0.085
                                                                                                                                                 -0.072 -0.069 -0.067 -0.038 -0.013 0.32 -0.39 0.15 0.33 -0.44 0.22
                                                                                                               0.074 0.11 0.17 0.76 -0.13 -0.072 1 -0.033 -0.035 -0.057 -0.016 0.045 -0.04 -0.02 0.015 -0.0034 -0.03
                                                                                                               0.051 0.39 0.038 0.11 0.27 -0.069 -0.033
       fronttyre_speed - 0.46 0.068 0.24 -0.11 0.16 -0.19 0.029 0.2 -0.28 0.066 0.38 0.12 0.11 0.16 0.24
                                                                                                                                                                               -0.19 0.18 0.062 -0.2 0.18 0.061
 Rear tire_construction_B - -0.47 -0.05 -0.35 0.23 -0.24 0.26 -0.0082 -0.074 0.2 -0.16 -0.44 -0.29 -0.16 -0.23 -0.33
                                                                                                               -0.045 -0.48 -0.12 -0.13 -0.36 -0.038 -0.057
Front tire_construction_B - -0.45 -0.046 -0.33 -0.21 -0.23 -0.27 -0.035 -0.043 -0.19 -0.18 -0.45 -0.24 -0.15 -0.22 -0.31
                                                                                                               -0.059 -0.47 -0.096 -0.12 -0.39 -0.013 -0.016
                                                                                                                                                                               -0.17 0.16 0.057 -0.18 0.17 0.067
                                                                                                               -0.094 -0.36 -0.53 -0.038 -0.39 -0.39 -0.04 -0.12 -0.12 0.18 0.16 -0.94 1
 Rear tire_label_format_N = -0.14 -0.15 -0.35 0.25 -0.21 0.26 -0.063 0.027 0.017 -0.061 -0.26 -0.16 -0.24 -0.15 -0.33
                                                                                                               0.049 -0.037 0.089 -0.012 0.047 0.15 -0.02 -0.042 -0.042 0.062 0.057 -0.33 -0.014
 Rear tire_label_format_A --0.0032 0.009 0.017 0.0099 -0.081 0.1 -0.025 -0.09 0.12 -0.026 -0.057 0.051 0.012 0.07 0.025
                                                                                                               0.071 0.36 0.42 0.019 0.37 0.33 0.015 0.14 0.14 -0.2 -0.18
Front tire_label_format_N = -0.14 -0.14 -0.35 0.26 -0.22 0.28 -0.067 0.032 0.0098 -0.059 -0.26 -0.17 -0.23 -0.16 -0.33
                                                                                                               -0.11 -0.38 -0.49 -0.013 -0.43 -0.44 -0.0034 -0.13 -0.13 0.18 0.17
```

```
In [ ]:
    corr_matrix = df_feats.corr()
    my_cmap = sns.diverging_palette(20, 20, as_cmap=True)
    fig, ax = plt.subplots(figsize=(30,30))
    heatmap = sns.heatmap(corr_matrix, vmin=-1, vmax=1, annot=True, square=True, cmap=my_cmap, ax=ax)
    heatmap.set_title('Correlation matrix')
```

Out[]: Text(0.5, 1.0, 'Correlation matrix')

1. Neural Network Hyperparameters (a) Design and conduct your experiment (Code)

There are 9 models below (hidden_layer_size; activation_function):\ 10,5; relu\ 10,5; tanh\ 10,5; identity\ 10,10; relu\ 10,10; tanh\ 10,10; identity\ 20,5; relu\ 20,5; tanh\ 20,5; identity

(1625, 43) (1625, 9) (697, 43) (697, 9)

```
In [ ]: #Initilaize model 1
        num=1
        Model_num = MLPClassifier(hidden_layer_sizes=(10,5), activation='relu',max_iter=20000, alpha=0.01,
                           solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion matrix=cm, display labels=label names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 1 results:

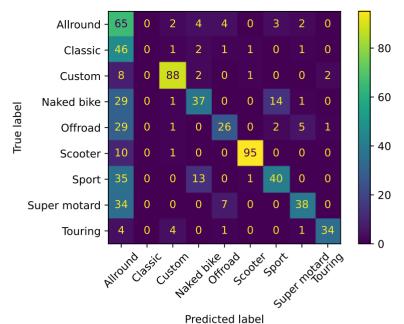
| Model I I | esur | ι. | | | |
|-----------|------|-----------|--------|----------|---------|
| | | precision | recall | f1-score | support |
| | | | | | |
| | 0 | 0.69 | 0.30 | 0.42 | 80 |
| | 1 | 0.00 | 0.00 | 0.00 | 52 |
| | 2 | 0.90 | 0.87 | 0.88 | 101 |
| | 3 | 0.64 | 0.45 | 0.53 | 82 |
| | 4 | 0.64 | 0.45 | 0.53 | 64 |
| | 5 | 0.96 | 0.90 | 0.93 | 106 |
| | 6 | 0.68 | 0.49 | 0.57 | 89 |
| | 7 | 0.80 | 0.54 | 0.65 | 79 |
| | 8 | 0.80 | 0.80 | 0.80 | 44 |
| | | | | | |
| micro | avg | 0.79 | 0.57 | 0.66 | 697 |
| macro | avg | 0.68 | 0.53 | 0.59 | 697 |
| weighted | avg | 0.72 | 0.57 | 0.62 | 697 |
| samples | avg | 0.55 | 0.57 | 0.56 | 697 |
| | | | | | |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division ` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.

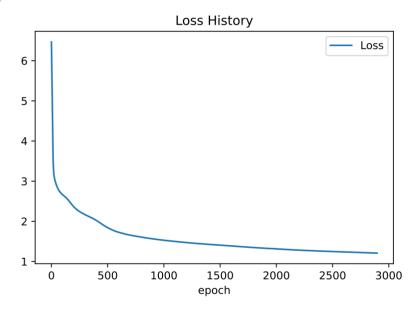
_warn_prf(average, modifier, msg_start, len(result))



Tredicted

accuracy is 0.5437589670014347

Out[]: <matplotlib.legend.Legend at 0x2167fb2b7c0>



```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(10,5), activation='tanh',max_iter=20000, alpha=0.01,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        \verb|cm| = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_||
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
```

```
plt.plot(h.loss_curve_)
plt.title('Loss History')
plt.xlabel('epoch')
plt.legend(['Loss'])
```

Model 2 results:

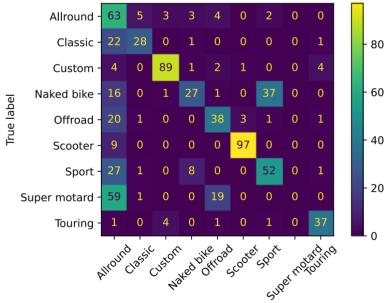
| | | precision | recall | f1-score | support |
|----------|-----|-----------|--------|----------|---------|
| | | | | | |
| | 0 | 0.00 | 0.00 | 0.00 | 80 |
| | 1 | 0.78 | 0.54 | 0.64 | 52 |
| | 2 | 0.92 | 0.88 | 0.90 | 101 |
| | 3 | 0.68 | 0.33 | 0.44 | 82 |
| | 4 | 0.58 | 0.59 | 0.59 | 64 |
| | 5 | 0.96 | 0.92 | 0.94 | 106 |
| | 6 | 0.55 | 0.58 | 0.57 | 89 |
| | 7 | 0.00 | 0.00 | 0.00 | 79 |
| | 8 | 0.82 | 0.84 | 0.83 | 44 |
| | | | | | |
| micro | avg | 0.77 | 0.53 | 0.63 | 697 |
| macro | avg | 0.59 | 0.52 | 0.54 | 697 |
| weighted | avg | 0.59 | 0.53 | 0.55 | 697 |
| samples | avg | 0.53 | 0.53 | 0.53 | 697 |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division ` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))



Predicted label

accuracy is 0.5279770444763271

<matplotlib.legend.Legend at 0x21602022b50>

Out[]:

Loss History Loss 6 5 4 3 2 1 0 500 1000 1500 2000 2500 3000 3500

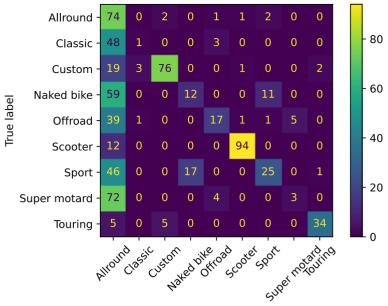
epoch

```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(10,5), activation='identity',max_iter=20000, alpha=0.01,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----
                               -----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 3 results:

```
recall f1-score
              precision
                                               support
           0
                   0.00
                             0.00
                                       0.00
                                                    80
           1
                   0.14
                             0.02
                                       0.03
                                                    52
           2
                   0.91
                             0.78
                                       0.84
                                                   101
           3
                   0.40
                             0.15
                                       0.21
                                                    82
           4
                   0.66
                             0.30
                                       0.41
                                                    64
           5
                   0.95
                             0.89
                                       0.92
                                                   106
           6
                   0.67
                             0.46
                                       0.55
           7
                   0.29
                             0.06
                                       0.10
                                                    79
           8
                   0.86
                             0.82
                                       0.84
                                                    44
                   0.77
                             0.41
                                        0.54
                                                   697
   micro avg
                             0.39
                                       0.43
                                                   697
   macro avg
                   0.54
weighted avg
                   0.57
                             0.41
                                        0.46
                                                   697
 samples avg
                   0.38
                             0.41
                                        0.39
                                                   697
```

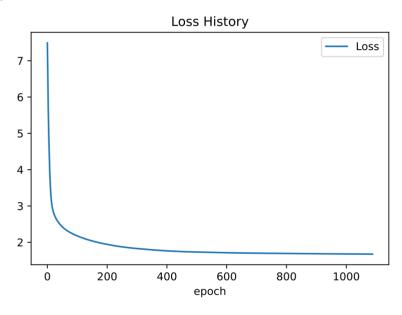
c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))



Predicted label

accuracy is 0.35581061692969873

Out[]: <matplotlib.legend.Legend at 0x2160cce3a30>



```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(10,10), activation='relu',max_iter=20000, alpha=0.01,
                           solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
```

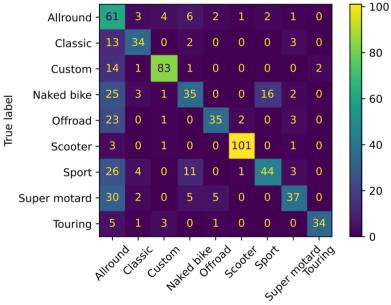
```
plt.plot(h.loss_curve_)
plt.title('Loss History')
plt.xlabel('epoch')
plt.legend(['Loss'])
```

Model 4 results:

| | | precision | recall | f1-score | support |
|-------------|----|-----------|--------|----------|---------|
| | | | | | |
| | 0 | 0.79 | 0.61 | 0.69 | 80 |
| | 1 | 0.68 | 0.65 | 0.67 | 52 |
| | 2 | 0.89 | 0.84 | 0.87 | 101 |
| | 3 | 0.54 | 0.46 | 0.50 | 82 |
| | 4 | 0.74 | 0.55 | 0.63 | 64 |
| | 5 | 0.96 | 0.95 | 0.96 | 106 |
| | 6 | 0.70 | 0.53 | 0.60 | 89 |
| | 7 | 0.76 | 0.52 | 0.62 | 79 |
| | 8 | 0.87 | 0.77 | 0.82 | 44 |
| | | | | | |
| micro av | vg | 0.79 | 0.67 | 0.72 | 697 |
| macro av | vg | 0.77 | 0.65 | 0.71 | 697 |
| weighted av | vg | 0.78 | 0.67 | 0.72 | 697 |
| samples av | vg | 0.65 | 0.67 | 0.66 | 697 |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

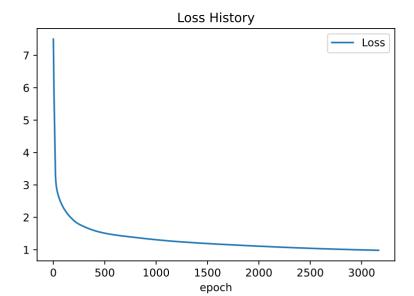
_warn_prf(average, modifier, msg_start, len(result))



Predicted label

accuracy is 0.6341463414634146

Out[]: <matplotlib.legend.Legend at 0x2160ce8b520>

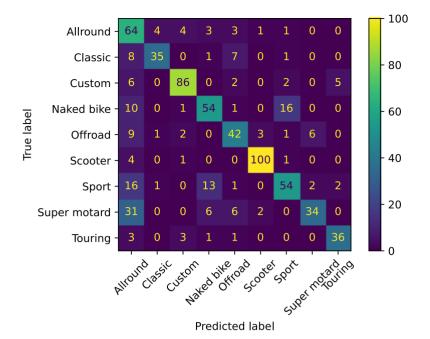


```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(10,10), activation='tanh',max_iter=20000, alpha=0.01,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----
                              -----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 5 results:

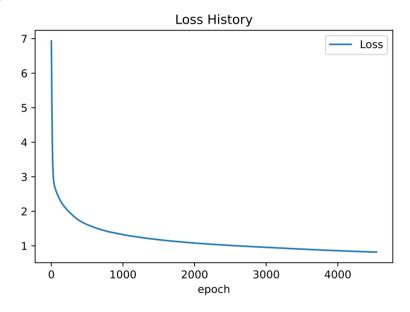
```
recall f1-score
              precision
                                              support
           0
                   0.82
                             0.70
                                       0.76
                                                    80
           1
                   0.83
                             0.67
                                       0.74
                                                    52
           2
                   0.89
                             0.85
                                       0.87
                                                   101
           3
                   0.69
                             0.66
                                       0.68
                                                    82
           4
                   0.67
                             0.66
                                       0.66
                                                   64
           5
                   0.94
                             0.94
                                       0.94
                                                  106
           6
                   0.69
                             0.63
                                       0.66
           7
                   0.73
                             0.44
                                       0.55
                                                   79
           8
                   0.77
                             0.82
                                       0.79
                                                   44
                   0.79
                             0.72
                                       0.75
                                                   697
   micro avg
                             0.71
                                       0.74
                   0.78
                                                   697
   macro avg
weighted avg
                   0.79
                             0.72
                                       0.75
                                                   697
 samples avg
                   0.71
                             0.72
                                       0.71
                                                   697
```

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.6987087517934003

Out[]: <matplotlib.legend.Legend at 0x2160ea68760>



```
In [ ]: #model initialization
        num=6
        Model_num = MLPClassifier(hidden_layer_sizes=(10,10), activation='identity',max_iter=20000, alpha=0.01,
                           solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
```

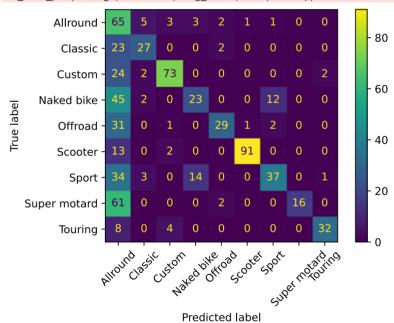
```
plt.plot(h.loss_curve_)
plt.title('Loss History')
plt.xlabel('epoch')
plt.legend(['Loss'])
```

Model 6 results:

| | | precision | recall | f1-score | support |
|----------|-----|-----------|--------|----------|---------|
| | 0 | 0.47 | 0.09 | 0.15 | 80 |
| | 1 | 0.70 | 0.54 | 0.61 | 52 |
| | 2 | 0.88 | 0.74 | 0.81 | 101 |
| | 3 | 0.57 | 0.28 | 0.38 | 82 |
| | 4 | 0.77 | 0.47 | 0.58 | 64 |
| | 5 | 0.93 | 0.88 | 0.90 | 106 |
| | 6 | 0.69 | 0.49 | 0.58 | 89 |
| | 7 | 0.64 | 0.20 | 0.31 | 79 |
| | 8 | 0.81 | 0.80 | 0.80 | 44 |
| | | | | | |
| micro | avg | 0.78 | 0.50 | 0.61 | 697 |
| macro | avg | 0.72 | 0.50 | 0.57 | 697 |
| weighted | avg | 0.73 | 0.50 | 0.57 | 697 |
| samples | avg | 0.48 | 0.50 | 0.49 | 697 |

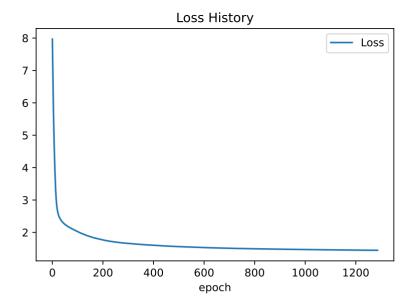
c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

_warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.45480631276901007

 ${\tt Out[\]:} \ \mbox{\tt <matplotlib.legend.Legend at 0x2160ee0bdc0>}$

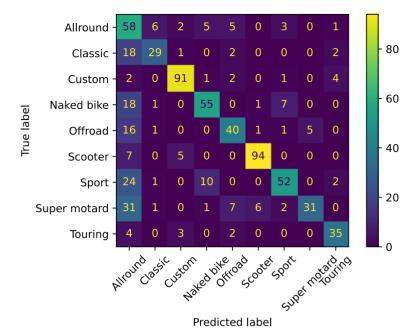


```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(20,5), activation='relu',max_iter=20000, alpha=0.01,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----
                              -----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 7 results:

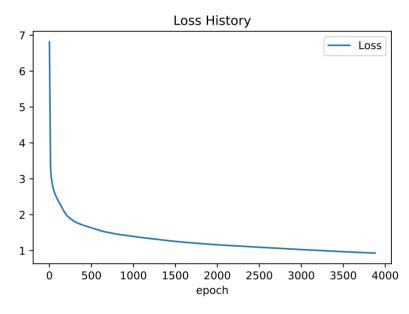
```
recall f1-score
              precision
                                              support
           0
                   0.85
                             0.42
                                       0.57
                                                   80
           1
                   0.74
                             0.56
                                       0.64
                                                   52
           2
                   0.88
                             0.90
                                       0.89
                                                   101
           3
                   0.73
                             0.67
                                       0.70
                                                   82
           4
                   0.67
                             0.64
                                       0.66
                                                   64
           5
                   0.92
                             0.92
                                       0.92
                                                  106
           6
                   0.70
                             0.64
                                       0.67
           7
                   0.62
                             0.42
                                       0.50
                                                   79
           8
                   0.77
                             0.82
                                       0.79
                                                   44
                   0.78
                             0.68
                                       0.73
                                                   697
   micro avg
                                       0.70
                   0.77
                             0.67
                                                   697
   macro avg
weighted avg
                   0.78
                             0.68
                                       0.72
                                                   697
 samples avg
                   0.66
                             0.68
                                       0.66
                                                   697
```

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.6327116212338594

Out[]: <matplotlib.legend.Legend at 0x2160ee00f40>



```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(20,5), activation='tanh',max_iter=20000, alpha=0.01,
                           solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
```

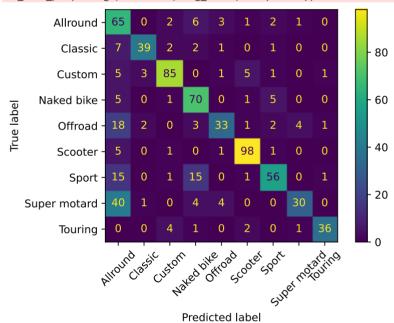
```
plt.plot(h.loss_curve_)
plt.title('Loss History')
plt.xlabel('epoch')
plt.legend(['Loss'])
```

Model 8 results:

| | | precision | recall | f1-score | support |
|----------|-----|-----------|--------|----------|---------|
| | 0 | 0.81 | 0.71 | 0.76 | 80 |
| | 1 | 0.82 | 0.77 | 0.79 | 52 |
| | 2 | 0.88 | 0.84 | 0.86 | 101 |
| | 3 | 0.67 | 0.85 | 0.75 | 82 |
| | 4 | 0.73 | 0.55 | 0.62 | 64 |
| | 5 | 0.88 | 0.92 | 0.90 | 106 |
| | 6 | 0.76 | 0.64 | 0.70 | 89 |
| | 7 | 0.83 | 0.38 | 0.52 | 79 |
| | 8 | 0.75 | 0.86 | 0.80 | 44 |
| | | | | | |
| micro | avg | 0.79 | 0.73 | 0.76 | 697 |
| macro | avg | 0.79 | 0.73 | 0.74 | 697 |
| weighted | avg | 0.80 | 0.73 | 0.75 | 697 |
| samples | avg | 0.72 | 0.73 | 0.72 | 697 |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

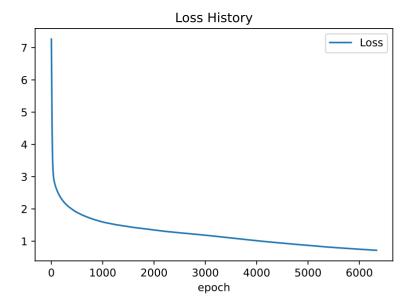
_warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.7058823529411765

Out[]:

<matplotlib.legend.Legend at 0x216107a8df0>

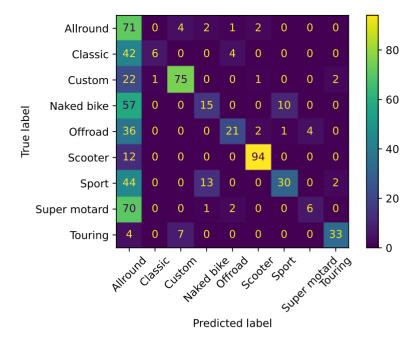


```
In [ ]: #model initialization
        Model_num = MLPClassifier(hidden_layer_sizes=(20,5), activation='identity',max_iter=20000, alpha=0.01,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----
                              -----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 9 results:

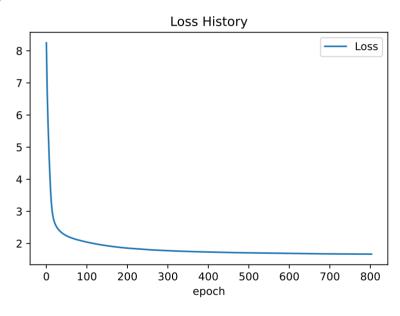
```
recall f1-score
              precision
                                               support
           0
                   0.00
                             0.00
                                       0.00
                                                    80
           1
                   0.86
                             0.12
                                       0.20
                                                    52
           2
                   0.87
                             0.75
                                       0.81
                                                   101
           3
                   0.48
                             0.18
                                       0.27
                                                    82
           4
                   0.70
                             0.33
                                       0.45
                                                    64
           5
                   0.92
                             0.89
                                       0.90
                                                   106
           6
                   0.68
                             0.44
                                       0.53
           7
                             0.08
                   0.35
                                       0.12
                                                    79
           8
                   0.80
                             0.82
                                       0.81
                                                    44
                   0.78
                             0.42
                                        0.55
                                                   697
   micro avg
                             0.40
                                       0.46
                                                   697
   macro avg
                   0.63
weighted avg
                   0.63
                             0.42
                                        0.48
                                                   697
 samples avg
                   0.40
                             0.42
                                        0.41
                                                   697
```

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.381635581061693

Out[]: <matplotlib.legend.Legend at 0x216107a8ac0>



(b) Report your methods, results, and analysis (Report)

- The dataset was downloaded from Github. It was preprocessed and the number for features were properly standarized and flattened. Number of features is pretty high and I suppose this is why the model had problems with performance unless I increased the number of iterations for batch size, decreased learning rate and also made the number of layers significantly bigger (from 10 the lowest to 75 the highest).
- The results of nine models are summarized here:

| | relu | tanh | identity |
|----------|-----------|---------|----------|
| Learning | rate 0.01 | | |
| 10,5 | 54% (1) | 53% (2) | 36% (3) |
| 10,10 | 63% (4) | 70% (5) | 45% (6) |
| 20,5 | 63% (7) | 71% (8) | 38% (9) |

From the results, it can be concluded that tanh did the best job across all activation functions, then relu but identity so simple linear function did not give any good results and did actually poorer than even random 50% of accuracy. I wanted to choose the dataset that would not be that easy for the model. After building the simple models on easy datasets like iris, I wanted to experiment with more complex features. Since this model has 43 features, I suspect that sone of the reasons the model did so poorly. However, also the features are more correlated as the heatmaps showed so the model with more hidden layers does obviously better. There is more added complexity with every following feature and, therefore, every following layer. Also, not surprisingly, the simple linear function is not able to capture the interconnectivity of the high number of features.

The model cofuses mostly 'Allround' category of motorcycles which also has a reasonable explanation. This category will have most of the features and as long as the model is simple (less hidden layers) and the learning rate is lower, the model does not learn (explore) enough to recognize the difference between the generic 'Allround' category and other more specific categories. That's why we see a lot of FP and FN in the confusion marix for 'Allround' category.

Another interesting observation is that the categories that are being confused a lot are: "Sport" and "Naked bikes". It makes absolutely sense since the difference is not in the very technical specifications of the motorcycle types but rather in the way they are designed and the way they look (the engine is covered or not). But the specifications can remain very similar. The confusion martix shows also these observations.

More exploration of models

The increase in performance led me to further exploration with learning rates and number of layers.

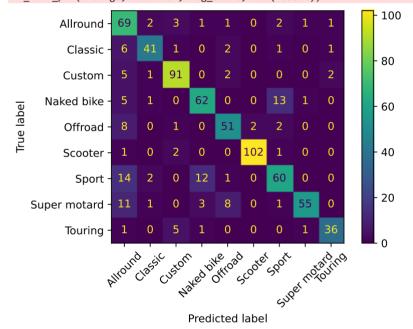
```
In [ ]: # Best model with 30 layers and smaller learning rate
        #model initialization
        num=10
       Model_num = MLPClassifier(hidden_layer_sizes=(30,30), activation='tanh',max_iter=20000, alpha=0.0001,
                           solver='sgd', verbose=0, random_state=121)
        #train our model
       h=Model_num.fit(x_train,y_train)
        #use our model to predict
       y_pred_num=Model_num.predict(x_test)
        print("-----\n")
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        \verb|cm| = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_|)|
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
       plt.xticks(rotation=45)
       plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        print("\n-----
        plt.plot(h.loss curve )
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 10 results:

| | | precision | recall | f1-score | support |
|----------|-----|-----------|--------|----------|---------|
| | 0 | 0.81 | 0.79 | 0.80 | 80 |
| | | | | | |
| | 1 | 0.86 | 0.81 | 0.83 | 52 |
| | 2 | 0.88 | 0.91 | 0.89 | 101 |
| | 3 | 0.78 | 0.76 | 0.77 | 82 |
| | 4 | 0.77 | 0.80 | 0.78 | 64 |
| | 5 | 0.97 | 0.98 | 0.98 | 106 |
| | 6 | 0.72 | 0.69 | 0.70 | 89 |
| | 7 | 0.86 | 0.77 | 0.81 | 79 |
| | 8 | 0.80 | 0.84 | 0.82 | 44 |
| | | | | | |
| micro | avg | 0.84 | 0.82 | 0.83 | 697 |
| macro | avg | 0.83 | 0.82 | 0.82 | 697 |
| weighted | avg | 0.83 | 0.82 | 0.83 | 697 |
| samples | avg | 0.80 | 0.82 | 0.81 | 697 |
| | | | | | |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

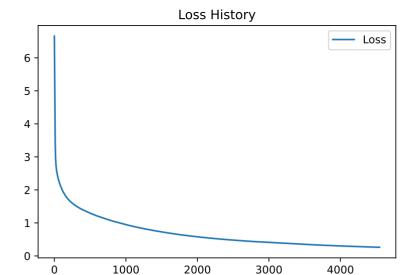
_warn_prf(average, modifier, msg_start, len(result))



accuracy is 0.787661406025825

<matplotlib.legend.Legend at 0x21610817460>

Out[]:



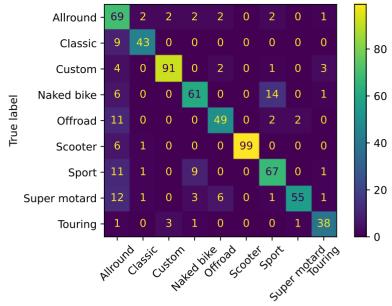
epoch

```
In [ ]: # Best model with 50 layers and smaller learning rate
        #model initialization
        num=11
        Model_num = MLPClassifier(hidden_layer_sizes=(50,50), activation='tanh',max_iter=20000, alpha=0.000001,
                            solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
        print("\n-----
        plt.plot(h.loss_curve_)
        plt.title('Loss History')
        plt.xlabel('epoch')
        plt.legend(['Loss'])
```

Model 11 results:

| | | precision | recall | f1-score | support |
|------------|-----|-----------|--------|----------|---------|
| | 0 | 0.85 | 0.80 | 0.83 | 80 |
| | 1 | 0.88 | 0.83 | 0.85 | 52 |
| | 2 | 0.94 | 0.90 | 0.92 | 101 |
| | 3 | 0.79 | 0.76 | 0.77 | 82 |
| | 4 | 0.82 | 0.77 | 0.79 | 64 |
| | 5 | 1.00 | 0.93 | 0.97 | 106 |
| | 6 | 0.74 | 0.76 | 0.75 | 89 |
| | 7 | 0.91 | 0.75 | 0.82 | 79 |
| | 8 | 0.81 | 0.86 | 0.84 | 44 |
| | | | | | |
| micro a | ıvg | 0.87 | 0.82 | 0.84 | 697 |
| macro a | ıvg | 0.86 | 0.82 | 0.84 | 697 |
| weighted a | ıvg | 0.87 | 0.82 | 0.84 | 697 |
| samples a | ıvg | 0.81 | 0.82 | 0.81 | 697 |

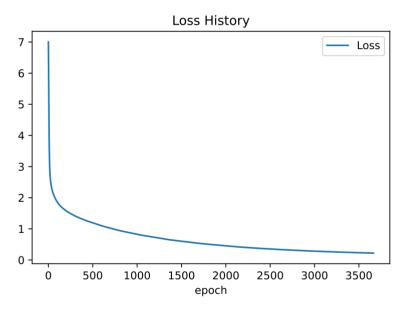
c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre
cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division
` parameter to control this behavior.
 _warn_prf(average, modifier, msg_start, len(result))



Predicted label

accuracy is 0.8005738880918221

Out[]: <matplotlib.legend.Legend at 0x2160cc2fc70>



```
In [ ]: # Best model with 75 layers and smaller learning rate
        #model initialization
        num=12
        Model_num = MLPClassifier(hidden_layer_sizes=(75,75), activation='tanh',max_iter=20000, alpha=0.000001,
                             solver='sgd', verbose=0, random_state=121)
        #train our model
        h=Model_num.fit(x_train,y_train)
        #use our model to predict
        y_pred_num=Model_num.predict(x_test)
        print("-----
        print(f"Model {num} results:")
        print(classification_report(y_test,y_pred_num))
        cm = confusion_matrix(y_test.argmax(axis=1), y_pred_num.argmax(axis=1), labels = Model_num.classes_)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=label_names)
        disp.plot()
        plt.xticks(rotation=45)
        plt.show()
        print('accuracy is ',accuracy_score(y_pred_num,y_test))
```

```
print("\n----")

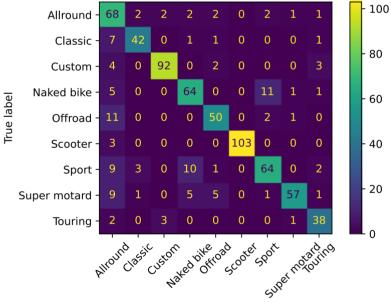
plt.plot(h.loss_curve_)
plt.title('Loss History')
plt.xlabel('epoch')
plt.legend(['Loss'])
```

Model 12 results:

| | | precision | recall | f1-score | support |
|----------|-----|-----------|--------|----------|---------|
| | | | | | |
| | 0 | 0.83 | 0.84 | 0.83 | 80 |
| | 1 | 0.86 | 0.81 | 0.83 | 52 |
| | 2 | 0.95 | 0.91 | 0.93 | 101 |
| | 3 | 0.76 | 0.78 | 0.77 | 82 |
| | 4 | 0.82 | 0.78 | 0.80 | 64 |
| | 5 | 0.97 | 0.97 | 0.97 | 106 |
| | 6 | 0.77 | 0.75 | 0.76 | 89 |
| | 7 | 0.87 | 0.76 | 0.81 | 79 |
| | 8 | 0.73 | 0.86 | 0.79 | 44 |
| | | | | | |
| micro | avg | 0.85 | 0.84 | 0.84 | 697 |
| macro | avg | 0.84 | 0.83 | 0.83 | 697 |
| weighted | avg | 0.85 | 0.84 | 0.84 | 697 |
| samples | avg | 0.82 | 0.84 | 0.83 | 697 |

c:\Users\natal\anaconda3\lib\site-packages\sklearn\metrics_classification.py:1221: UndefinedMetricWarning: Pre cision and F-score are ill-defined and being set to 0.0 in samples with no predicted labels. Use `zero_division ` parameter to control this behavior.

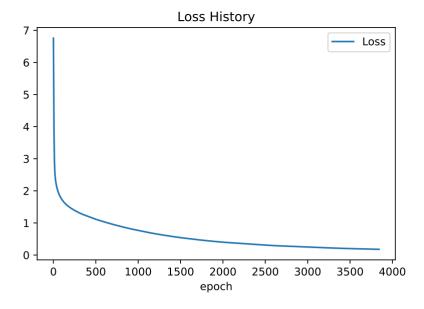
_warn_prf(average, modifier, msg_start, len(result))



Predicted label

accuracy is 0.812051649928264

Out[]: <matplotlib.legend.Legend at 0x21608e0de80>



Exploration results

| Learning | rate 0.0001 | |
|-------------------|---------------------------|--|
| 30,30 | 79% (10) | |
| | | |
| | | |
| Learning | rate 0.000001 | |
| Learning 50,50 | rate 0.000001 80% (11) | |

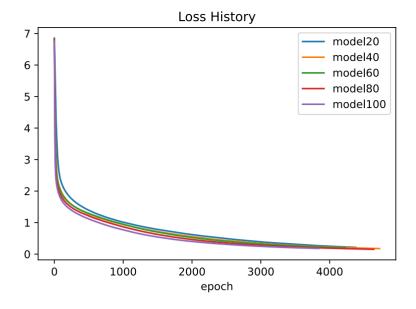
I decreased the laerning rate and increased the number of layers since this boosted the performance a lot. It just proves that more complex feature palette and bigger dataset requires more sophisticated models.

Splitting training set

1. Impact of Training Duration and Training Data (a) Design and conduct your experiment (Code)

```
In [ ]: # Splitting 70% of training data into further datasets
        x_train_20, x_train_80, y_train_20, y_train_80 = train_test_split(x_train, y_train, test_size=.8)
        x_train_40, x_train_60, y_train_40, y_train_60 = train_test_split(x_train, y_train, test_size=.6)
        # Checking if shapes are correct
        print("Features shapes:")
        print(x_train.shape)
        print(x_train_20.shape)
        print(x_train_40.shape)
        print(x_train_60.shape)
        print(x_train_80.shape)
        print('Labels shapes:')
        print(y_train.shape)
        print(y_train_20.shape)
        print(y_train_40.shape)
        print(y_train_60.shape)
        print(y_train_80.shape)
```

```
Features shapes:
                (1625, 43)
                (325, 43)
                (650, 43)
                (975, 43)
                (1300, 43)
               Labels shapes:
                (1625, 9)
                (325, 9)
                (650, 9)
                (975, 9)
                (1300, 9)
In [ ]: from traitlets.config.configurable import validate
                #Build model with the best results from the previous task
                Model = MLPClassifier(hidden_layer_sizes=(75,75), activation='tanh',max_iter=20000, alpha=0.000001,
                                                       solver='sgd', verbose=0, random_state=121)
                #train all models
                splits=[[x_train_20, y_train_20],[x_train_40, y_train_40],[x_train_60, y_train_60],[x_train_80, y_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[x_train_80],[
                for split in splits:
                       h=Model.fit(split[0],split[1])
                       #use our model to predict
                       y_pred=Model.predict(x_test)
                   # print model summary
                       print(f"Data shape: {split[0].shape}\nModel trained on {len(split[0]) / len(x_train) * 100} % of splitted tr
                       #print(confusion_matrix(y_test.argmax(axis=1), y_pred.argmax(axis=1))) # Print Confusion matrix
                       print('accuracy is ',accuracy_score(y_pred,y_test)) # Print accuracy score
                       print("\n----")
                       plt.plot(h.loss_curve_)
                       plt.title('Loss History')
                       plt.xlabel('epoch')
                       plt.legend(['model20','model40','model60','model80','model100'])
                -----
               Data shape: (325, 43)
               Model trained on 20.0 % of splitted training data (70/30):
               accuracy is 0.6083213773314203
               Data shape: (650, 43)
               Model trained on 40.0 % of splitted training data (70/30):
               accuracy is 0.7446197991391679
               Data shape: (975, 43)
               Model trained on 60.0 % of splitted training data (70/30):
               accuracy is 0.7403156384505022
               Data shape: (1300, 43)
               Model trained on 80.0 % of splitted training data (70/30):
               accuracy is 0.7790530846484935
                -----
                ______
               Data shape: (1625, 43)
               Model trained on 100.0 % of splitted training data (70/30):
               accuracy is 0.812051649928264
                ______
```



Results of splitting the training data

| Learning rate 0 | .0001 | |
|-----------------|----------|--|
| 30,30 | 79% (10) | |
| | | |
| Learning rate 0 | .000001 | |
| 50,50 | 80% (11) | |
| 75,75 | | |

(b) Report your methods, results, and analysis (Report)

- The best model found in the first part (20,5; tanh) was further checked and the final best model used in this case is: 75,75 for hidden layer, 0.000001 learning rate and tanh activation function.
- The model does a much better job while generalizing on bigger training set than on the train set that is reduced to 20, 40, 60 or 80% of the training set.