Ai_lab06_TahaAbbas_P200119

March 16, 2023

Lab Task 06 Multi layer Perceptron

Predicting Who Survived the Titanic Using Multilayer Perceptron (MLP)

The goal of this lab task is to build a multilayer perceptron (MLP) classifier that can predict whether a passenger survived the sinking of the Titanic or not.

1. Import the necessary Python libraries, such as pandas, numpy, and sklearn.
2. Load the Titanic dataset into a pandas DataFrame using pandas.read_csv().
3. Preprocess the data by converting categorical features into numerical ones, filling in missing values, and scaling the numerical features using sklearn.preprocessing.
4. Split the dataset into training and test sets using sklearn.model_selection.train_test_split().
5. Build an MLP classifier using sklearn.neural_network.MLPClassifier() and train it on the training data.
6. Evaluate the performance of the MLP classifier on the test data using metrics such as accuracy, precision, recall, and F1-score.
7. Fine-tune the MLP classifier by adjusting its hyperparameters, such as the number of hidden layers, and the number of neurons per layer.
8. Evaluate the performance of the fine-tuned MLP classifier on the test data and compare it to the initial model.
9. Discuss the results and insights gained from the experiment, and identify potential areas for further improvement.

[1]:
```
#imports
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
 ↪f1_score


# Visualization imports
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

[ ]:
```

```

[2]:
```
df = pd.read_csv('titanic_train.csv')
df.head()
```

[2]:
```
   passenger_id  pclass                                               name  \
0          1216       3                                Smyth, Miss. Julia
1           699       3                                   Cacic, Mr. Luka
2          1267       3  Van Impe, Mrs. Jean Baptiste (Rosalie Paula Go…
3           449       2              Hocking, Mrs. Elizabeth (Eliza Needs)
4           576       2                                   Veal, Mr. James

      sex   age  sibsp  parch  ticket     fare cabin embarked boat  body  \
0  female   NaN      0      0  335432   7.7333   NaN        Q   13   NaN
1    male  38.0      0      0  315089   8.6625   NaN        S  NaN   NaN
2  female  30.0      1      1  345773  24.1500   NaN        S  NaN   NaN
3  female  54.0      1      3   29105  23.0000   NaN        S    4   NaN
4    male  40.0      0      0   28221  13.0000   NaN        S  NaN   NaN

                  home.dest  survived
0                       NaN         1
1                   Croatia         0
2                       NaN         0
3      Cornwall / Akron, OH         1
4  Barre, Co Washington, VT         0
```

[3]:
```
df.shape
```

[3]:
```
(850, 15)
```

[4]:
```
df.columns
```

[4]:
```
Index(['passenger_id', 'pclass', 'name', 'sex', 'age', 'sibsp', 'parch',
       'ticket', 'fare', 'cabin', 'embarked', 'boat', 'body', 'home.dest',
       'survived'],
      dtype='object')
```

[5]:
```
df.describe()
```

[5]:
```
       passenger_id     pclass         age       sibsp       parch  \
count    850.000000  850.00000  676.000000  850.000000  850.000000
mean     662.816471    2.32000   29.519847    0.522353    0.382353
std      380.751936    0.83853   14.562243    1.112132    0.879511
min        1.000000    1.00000    0.166700    0.000000    0.000000
25%      332.250000    2.00000   20.000000    0.000000    0.000000
50%      676.500000    3.00000   28.000000    0.000000    0.000000
75%      992.250000    3.00000   37.000000    1.000000    0.000000
max     1307.000000    3.00000   80.000000    8.000000    9.000000
```

```
              fare        body    survived
count  849.000000   73.000000  850.000000
mean    34.012701  165.821918    0.368235
std     53.705779   99.068487    0.482610
min      0.000000    4.000000    0.000000
25%      7.895800   75.000000    0.000000
50%     14.108300  166.000000    0.000000
75%     31.000000  260.000000    1.000000
max    512.329200  328.000000    1.000000
```

[6]:
```
df.isnull().sum()
```

[6]:
```
passenger_id      0
pclass            0
name              0
sex               0
age             174
sibsp             0
parch             0
ticket            0
fare              1
cabin           659
embarked          1
boat            542
body            777
home.dest       386
survived          0
dtype: int64
```

[7]:
```
df.survived.value_counts()
```

[7]:
```
0    537
1    313
Name: survived, dtype: int64
```

[8]:
```
df.embarked.value_counts()
```

[8]:
```
S    589
C    176
Q     84
Name: embarked, dtype: int64
```

[9]:
```
df.pclass.value_counts()
```

[9]:
```
3    478
1    206
2    166
```

```
Name: pclass, dtype: int64
```

[10]:
```
label_encoder = LabelEncoder()

df['sex'] = label_encoder.fit_transform(df['sex'])
df['embarked'] = label_encoder.fit_transform(df['embarked'].astype(str))
df.head()
```

[10]:

	passenger_id	pclass	name	sex	age	sibsp	parch	ticket	fare	cabin	embarked	boat	body	home.dest	survived
0	1216	3	Smyth, Miss. Julia	0	NaN	0	0	335432	7.7333	NaN	1	13	NaN	NaN	1
1	699	3	Cacic, Mr. Luka	1	38.0	0	0	315089	8.6625	NaN	2	NaN	NaN	Croatia	0
2	1267	3	Van Impe, Mrs. Jean Baptiste (Rosalie Paula Go…	0	30.0	1	1	345773	24.1500	NaN	2	NaN	NaN	NaN	0
3	449	2	Hocking, Mrs. Elizabeth (Eliza Needs)	0	54.0	1	3	29105	23.0000	NaN	2	4	NaN	Cornwall / Akron, OH	1
4	576	2	Veal, Mr. James	1	40.0	0	0	28221	13.0000	NaN	2	NaN	NaN	Barre, Co Washington, VT	0

[11]:
```
# Select features and target variable
X = df[['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare', 'embarked']]
y = df['survived']
```

[12]:
```
X.head(10)
```

[12]:

	pclass	sex	age	sibsp	parch	fare	embarked
0	3	0	NaN	0	0	7.7333	1
1	3	1	38.0	0	0	8.6625	2
2	3	0	30.0	1	1	24.1500	2
3	2	0	54.0	1	3	23.0000	2
4	2	1	40.0	0	0	13.0000	2
5	3	1	28.0	0	0	22.5250	2
6	3	1	19.0	0	0	0.0000	2
7	2	0	30.0	0	0	13.0000	2
8	3	0	22.0	0	0	7.7750	2
9	3	0	21.0	1	0	9.8250	2

[13]:
```
X.isnull().sum()
```

[13]:
```
pclass        0
sex           0
age         174
sibsp         0
parch         0
fare          1
embarked      0
dtype: int64
```

[14]:
```
#df["age"] = df["age"].fillna(df["age"].mean())
```

[ ]:
```
X.fillna(X.mean(), inplace=True)
```

[16]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 850 entries, 0 to 849
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   pclass    850 non-null    int64  
 1   sex       850 non-null    int64  
 2   age       850 non-null    float64
 3   sibsp     850 non-null    int64  
 4   parch     850 non-null    int64  
 5   fare      850 non-null    float64
 6   embarked  850 non-null    int64  
dtypes: float64(2), int64(5)
memory usage: 46.6 KB
```

[ ]:
```
scaler = StandardScaler()

column = ['age', 'sibsp', 'parch', 'fare']
X[column] = scaler.fit_transform(X[column])
```

[18]:
```
X.head()
```

[18]:

	pclass	sex	age	sibsp	parch	fare	embarked
0	3	0	2.737723e-16	-0.469963	-0.434989	-0.489898	1
1	3	1	6.534810e-01	-0.469963	-0.434989	-0.472576	2
2	3	0	3.700060e-02	0.429741	0.702675	-0.183860	2
3	2	0	1.886442e+00	0.429741	2.978005	-0.205298	2
4	2	1	8.076011e-01	-0.469963	-0.434989	-0.391717	2

[19]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=10)
```

[20]:
```
X_train.head(3)
```

[20]:

	pclass	sex	age	sibsp	parch	fare	embarked
476	2	0	-1.966561	1.329444	0.702675	0.092973	2
411	3	1	-0.502420	-0.469963	-0.434989	-0.502636	2
377	1	0	-0.810660	-0.469963	1.840340	-0.144091	2

[21]:
```
X_test.head(3)
```

[21]:

	pclass	sex	age	sibsp	parch	fare	embarked
780	3	1	2.737723e-16	-0.469963	-0.434989	-0.471644	2
233	3	1	2.737723e-16	-0.469963	-0.434989	0.419128	2
68	3	1	-4.005945e-02	-0.469963	-0.434989	-0.457275	2

[22]:
```
y_train.value_counts()
```

[22]:
```
0    425
1    255
Name: survived, dtype: int64
```

[23]:
```
y_test.value_counts()
```

[23]:
```
0    112
1     58
Name: survived, dtype: int64
```

[24]:
```
mlp = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(8,6),␣
↪max_iter=1000, random_state=1)
mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)
```

Before Fine tunning

[25]:
```
print('Accuracy score:', round(accuracy_score(y_test, y_pred),2))
print('Precision score:', round(precision_score(y_test, y_pred),2))
print('Recall score:', round(recall_score(y_test, y_pred),2))
print('F1 score:', round( f1_score(y_test, y_pred),2))
```

```
Accuracy score: 0.78
Precision score: 0.75
Recall score: 0.52
F1 score: 0.61
```

[ ]:
```
mlp = MLPClassifier(solver='lbfgs', alpha=1e-5, hidden_layer_sizes=(8,8),␣
↪max_iter=1500, random_state=1)
mlp.fit(X_train, y_train)
y_pred = mlp.predict(X_test)
```

After tunning

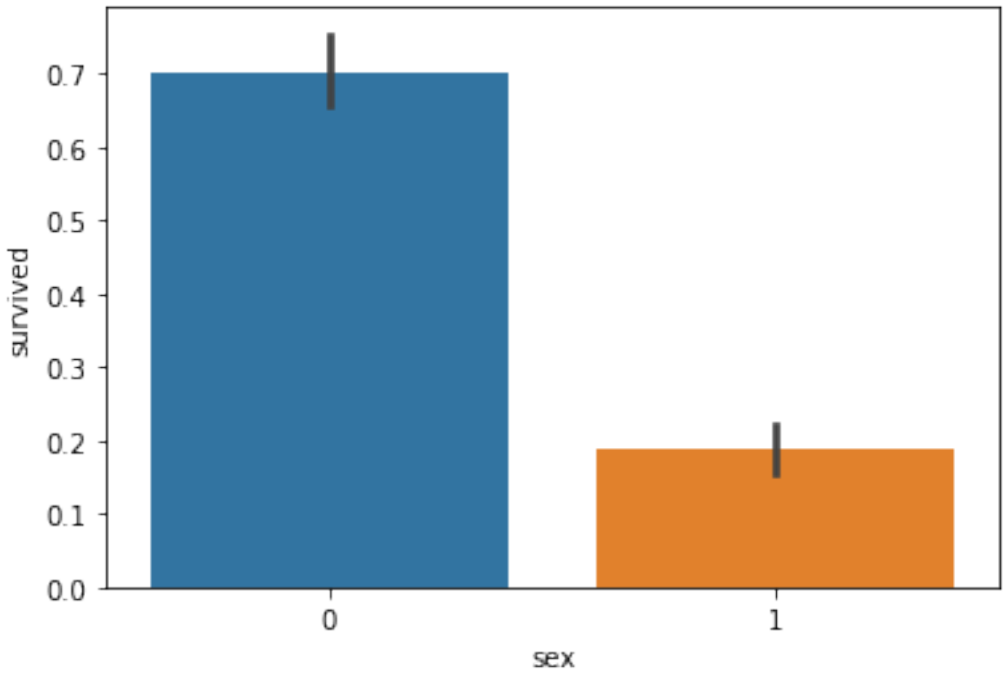
[27]:
```
print('Accuracy score:', round(accuracy_score(y_test, y_pred),2))
print('Precision score:', round(precision_score(y_test, y_pred),2))
print('Recall score:', round(recall_score(y_test, y_pred),2))
print('F1 score:', round( f1_score(y_test, y_pred),2))
```

```
Accuracy score: 0.79
Precision score: 0.78
Recall score: 0.55
F1 score: 0.65
```

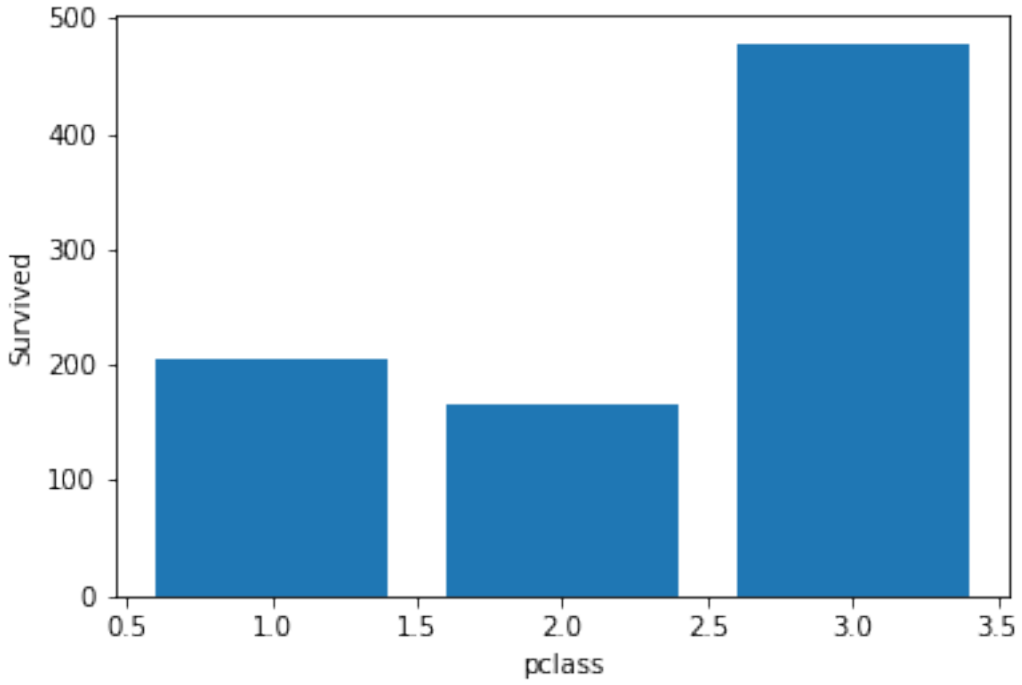
[28]:
```
Xlim = df[['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare', 'embarked',␣
↪'survived']]
```

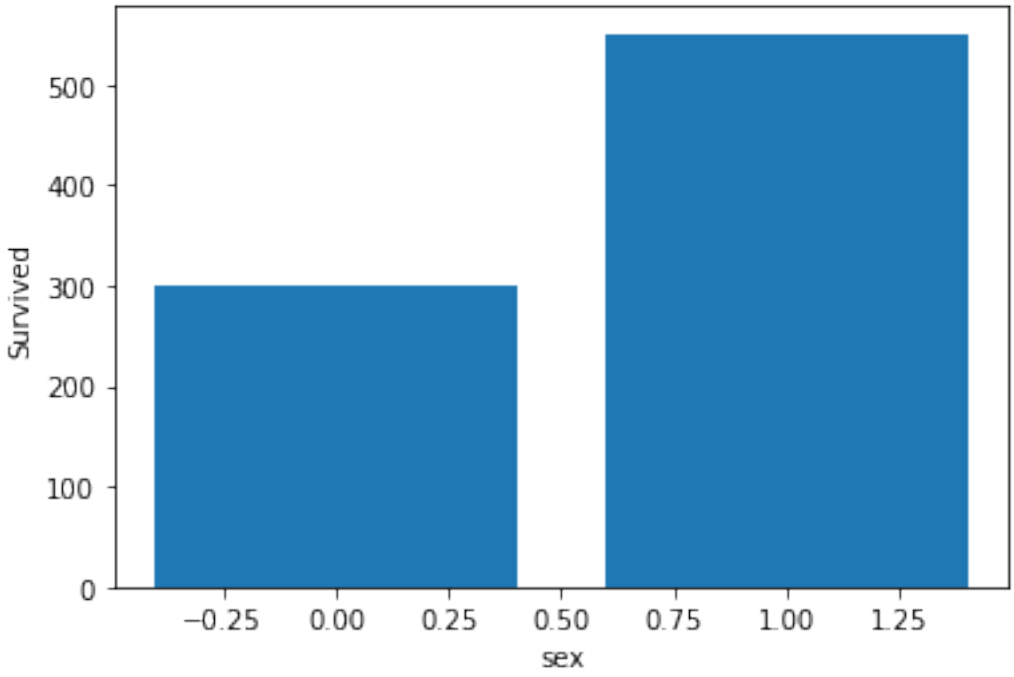
[29]:
```
sns.barplot(data=Xlim, x="sex", y="survived")
```

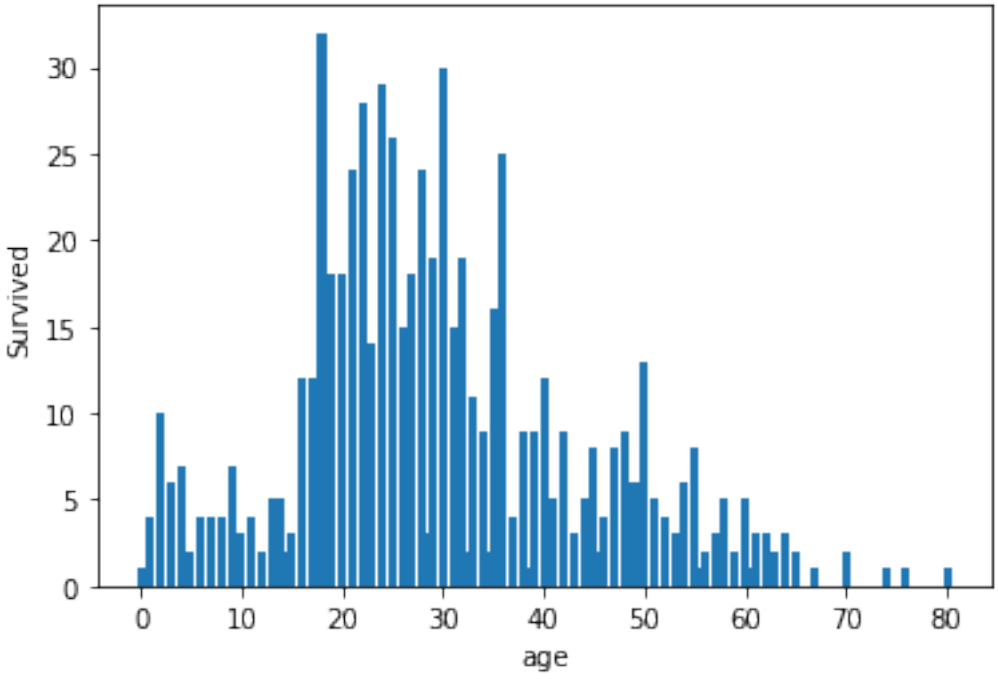
[29]:
```
<Axes: xlabel='sex', ylabel='survived'>
```

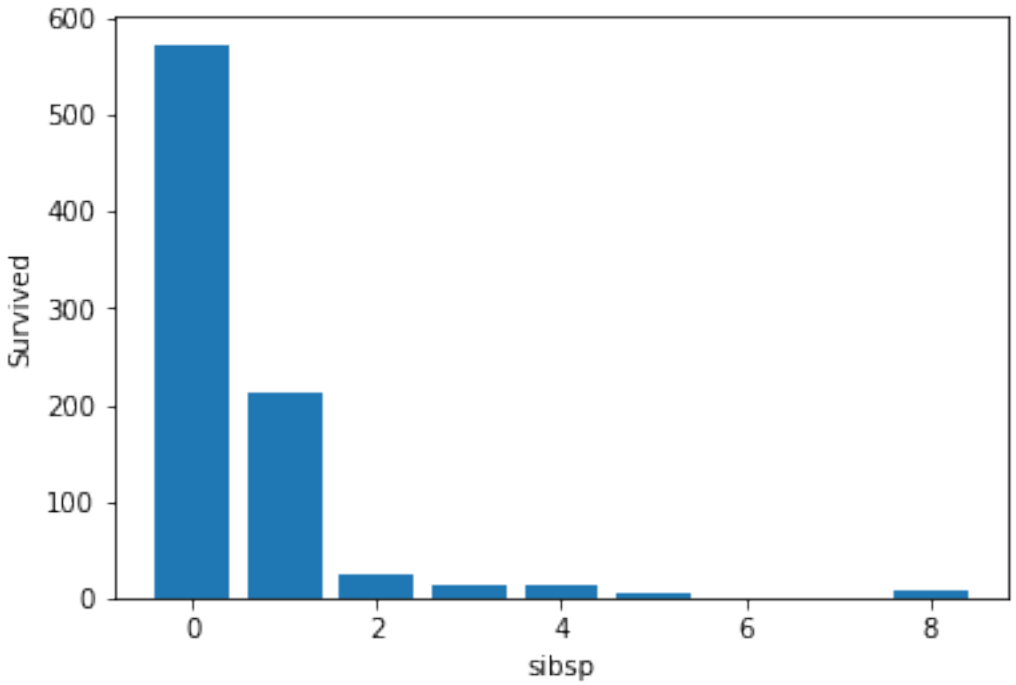


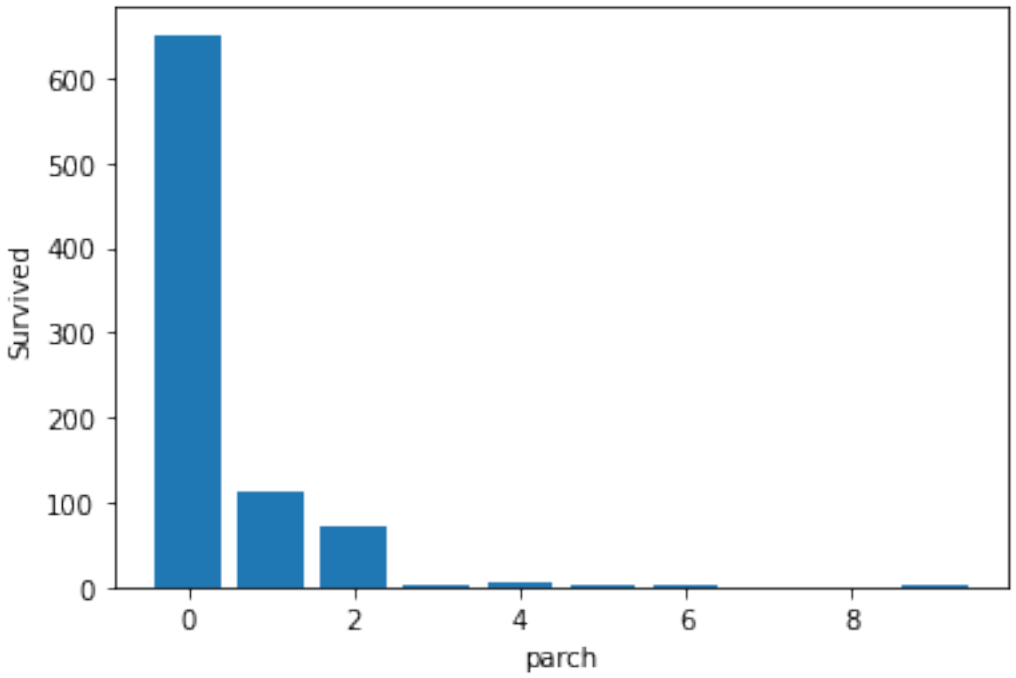
[30]:
```
for column in Xlim.columns:
        fig, ax = plt.subplots()
        ax.bar(df[column].value_counts().index, df[column].value_counts().
 ↪values)
        ax.set_xlabel(column)
        ax.set_ylabel('Survived')
        plt.show()
```

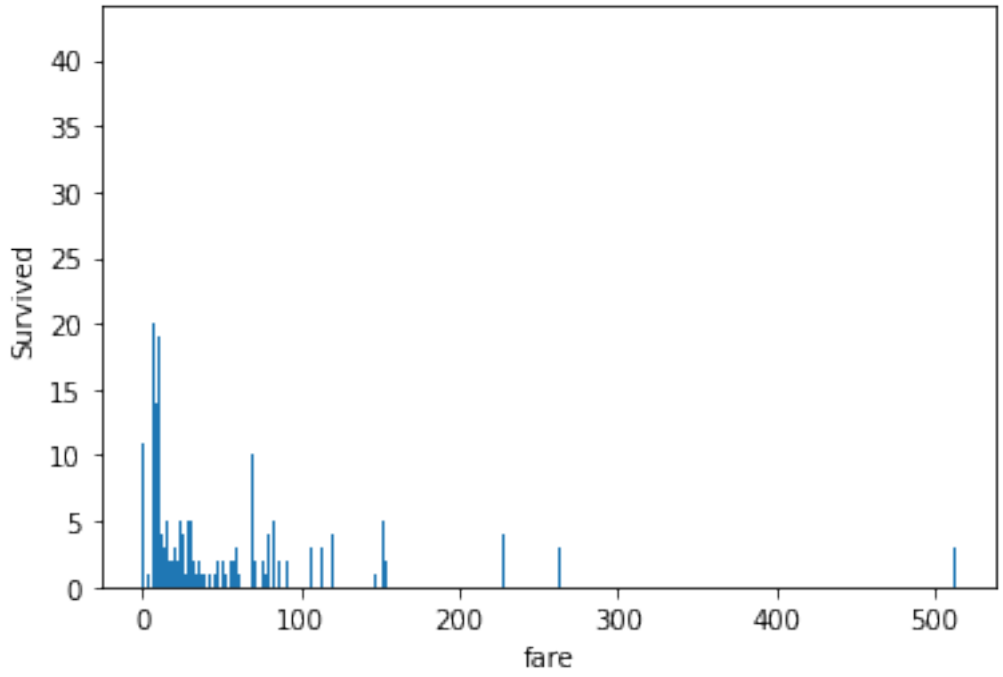


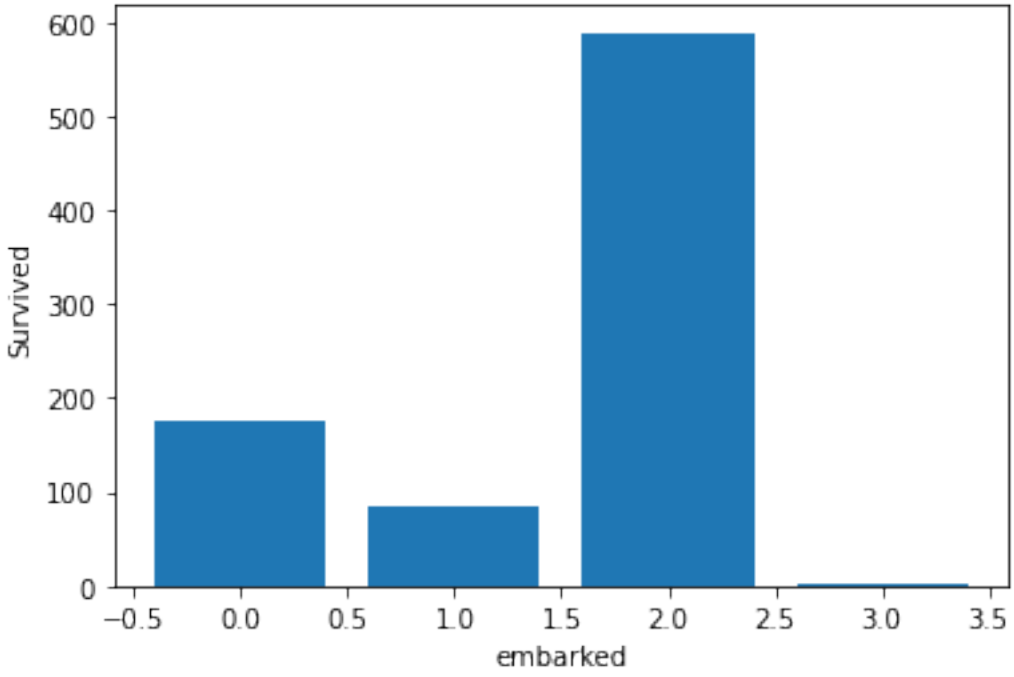

Survived
500
400
300
200
100
0
−0.25
0.00
0.25
0.50
0.75
1.00
1.25
sex

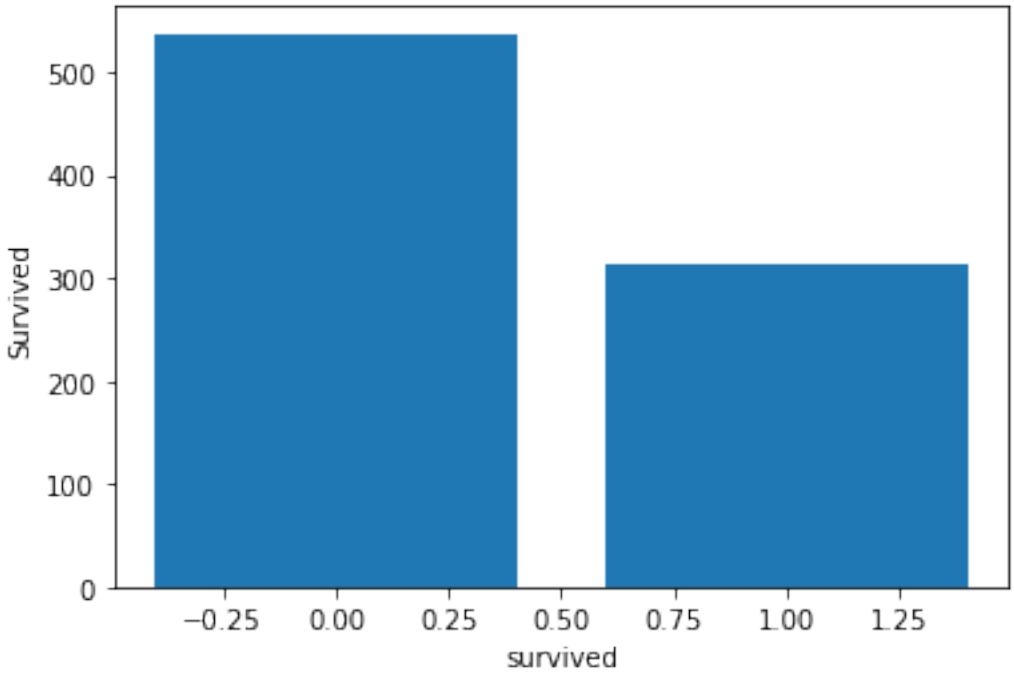

Survived
30
25
20
15
10
5
0
0
10
20
30
40
50
60
70
80
age


600
500
400
300
200
100
0
Survived
0
2
4
6
8
sibsp


600
500
400
300
200
100
0
Survived
0
2
4
6
8
parch


Survived
fare
0
5
10
15
20
25
30
35
40
0
100
200
300
400
500


Survived
embarked
0
100
200
300
400
500
600
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5



We can observe from the results that the fine-tuned model performs marginally better than the baseline MLP model in terms of accuracy, precision, recall, and F1-score. This shows that modifying the hyperparameters can enhance model performance, and that more feature engineering and data preparation may do the same.

[ ]: