

BUENAFE, Lorenz Angelo N.
1915058
CPE 019 - CPE32S9

Choose any dataset applicable to the classification problem, and also, choose any dataset applicable to the regression problem.

Classification - <https://www.kaggle.com/datasets/bharath011/heart-disease-classification-dataset>

Regression - <https://www.kaggle.com/datasets/anubhavgoyal10/laptop-prices-dataset>

Explain your datasets and the problem being addressed.

<https://www.kaggle.com/datasets/bharath011/heart-disease-classification-dataset>

The main purpose here is to collect characteristics of Heart Attack or factors that contribute to it.

<https://www.kaggle.com/datasets/anubhavgoyal10/laptop-prices-dataset>

This dataset can be used for regression analysis to predict the prices of laptops based on their features.

- For classification, do the following:
- Create a base model
 - Evaluate the model with k-fold cross validation
 - Improve the accuracy of your model by applying additional hidden layers

1. Creating a base model

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from sklearn.model_selection import cross_val_score

df = pd.read_csv('/content/drive/MyDrive/CPE 019 Emerging Technologies 3/Assignment 7.1/Heart Disease Classification Dataset.csv')

print(df.head)
```

	<bound	method	NDFrame.head of	age	gender	impluse	pressurehight	pressurelow	g
0	64	1	66	160		83	160.0	1.80	
1	21	1	94	98		46	296.0	6.75	
2	55	1	64	160		77	270.0	1.99	
3	64	1	70	120		55	270.0	13.87	
4	55	1	64	112		65	300.0	1.08	
...	
1314	44	1	94	122		67	204.0	1.63	
1315	66	1	84	125		55	149.0	1.33	
1316	45	1	85	168		104	96.0	1.24	
1317	54	1	58	117		68	443.0	5.80	
1318	51	1	94	157		79	134.0	50.89	

	troponin	class
0	0.012	negative
1	1.060	positive

```

2      0.003  negative
3      0.122  positive
4      0.003  negative
...      ...      ...
1314    0.006  negative
1315    0.172  positive
1316    4.250  positive
1317    0.359  positive
1318    1.770  positive

```

```
[1319 rows x 9 columns]>
```

```

X = df.iloc[:, 0:4].values
y = df.iloc[:, 4].values

```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```

# Feature scaling
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

```

```

mlp_classifier = MLPClassifier(hidden_layer_sizes=(50,), activation='relu', alpha=0.0001, b
mlp_classifier.fit(X_train, y_train)

```

```

/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.p
warnings.warn(

```

```

▼
MLPClassifier
MLPClassifier(batch_size=256, hidden_layer_sizes=(50,), max_iter=500)

```

2. Evaluate the model with k-fold cross validation:

```

k_fold = 10
accuracies = cross_val_score(estimator=mlp_classifier, X=X_train, y=y_train, cv=k_fold)

print(f"Accuracy: {accuracies.mean()*100:.2f}% ({accuracies.std()*100:.2f}%)"

```

```

/usr/local/lib/python3.10/dist-packages/sklearn/model_selection/_split.py:700: UserWarn
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.p
warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.p
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warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.p
warnings.warn(
Accuracy: 7.67% (2.28%)
/usr/local/lib/python3.10/dist-packages/sklearn/neural_network/_multilayer_perceptron.p
warnings.warn(

```

3. Improve the accuracy of your model by applying additional hidden layers:

```
mlp_classifier = MLPClassifier(hidden_layer_sizes=(50, 50, 50), activation='relu', alpha=0.
mlp_classifier.fit(X_train, y_train)

# Evaluate the model on the test set
y_pred = mlp_classifier.predict(X_test)

print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
print("\nClassification Report:")
print(classification_report(y_test, y_pred))
print("\nAccuracy Score:")
print(accuracy_score(y_test, y_pred))
```

69	0.00	0.00	0.00	10
70	0.11	0.09	0.10	11
71	0.00	0.00	0.00	5
72	0.50	0.20	0.29	5
73	0.00	0.00	0.00	2
74	0.00	0.00	0.00	5
75	0.29	0.28	0.29	18
76	0.00	0.00	0.00	11
77	0.33	0.33	0.33	3
78	0.00	0.00	0.00	5
79	0.00	0.00	0.00	11
80	0.29	0.44	0.35	9
81	0.17	0.12	0.14	8
82	0.00	0.00	0.00	6
83	0.00	0.00	0.00	4

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Unde
_warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344: Unde
warn_prf(average, modifier, msg_start, len(result))
```

For regression, do the following:

Create a base model

Improve the model by standardizing the dataset

Show tuning of layers and neurons (see evaluating small and larger networks)

1. Creating a base model

```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense

df = pd.read_csv('/content/drive/MyDrive/CPE 019 Emerging Technologies 3/Assignment 7.1/lap

# Remove unnecessary columns
df = df.drop(['rating', 'Number of Ratings', 'Number of Reviews'], axis=1)

# Convert categorical variables to numerical using one-hot encoding
df = pd.get_dummies(df)

# Split the dataset into features and target variable
X = df.drop('Price', axis=1)
y = df['Price']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the base model
model = Sequential()
model.add(Dense(64, activation='relu', input_dim=X_train.shape[1]))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='linear'))

# Compile the model
model.compile(loss='mean_squared_error', optimizer='adam')

# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=32, verbose=1)
```

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BUENAFE Assignment 7.1 : Classifications and Regression.ipynb - Colab

```
21/21 [=====] - 0s 2ms/step - loss: 4491283436.0000
Epoch 31/50
21/21 [=====] - 0s 3ms/step - loss: 4259766272.0000
Epoch 32/50
21/21 [=====] - 0s 3ms/step - loss: 4035402496.0000
Epoch 33/50
21/21 [=====] - 0s 3ms/step - loss: 3819402240.0000
Epoch 34/50
21/21 [=====] - 0s 3ms/step - loss: 3611685888.0000
Epoch 35/50
21/21 [=====] - 0s 3ms/step - loss: 3417762560.0000
Epoch 36/50
21/21 [=====] - 0s 3ms/step - loss: 3236983552.0000
Epoch 37/50
21/21 [=====] - 0s 3ms/step - loss: 3066659328.0000
Epoch 38/50
21/21 [=====] - 0s 3ms/step - loss: 2912227328.0000
Epoch 39/50
21/21 [=====] - 0s 3ms/step - loss: 2776074240.0000
Epoch 40/50
21/21 [=====] - 0s 2ms/step - loss: 2651009792.0000
Epoch 41/50
21/21 [=====] - 0s 4ms/step - loss: 2543217664.0000
Epoch 42/50
21/21 [=====] - 0s 3ms/step - loss: 2445088512.0000
Epoch 43/50
21/21 [=====] - 0s 3ms/step - loss: 2360356352.0000
Epoch 44/50
21/21 [=====] - 0s 3ms/step - loss: 2291592192.0000
Epoch 45/50
21/21 [=====] - 0s 3ms/step - loss: 2228399616.0000
Epoch 46/50
21/21 [=====] - 0s 3ms/step - loss: 2174241792.0000
Epoch 47/50
21/21 [=====] - 0s 4ms/step - loss: 2130108672.0000
Epoch 48/50
21/21 [=====] - 0s 4ms/step - loss: 2090958208.0000
Epoch 49/50
21/21 [=====] - 0s 5ms/step - loss: 2056573824.0000
Epoch 50/50
21/21 [=====] - 0s 4ms/step - loss: 2025516800.0000
<keras.src.callbacks.History at 0x7e9c1e17e9e0>
```

```
# Standardize the dataset
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Create a new model
model_scaled = Sequential()
model_scaled.add(Dense(64, activation='relu', input_dim=X_train_scaled.shape[1]))
model_scaled.add(Dense(32, activation='relu'))
model_scaled.add(Dense(1, activation='linear'))

# Compile and train the model
model_scaled.compile(loss='mean_squared_error', optimizer='adam')
model_scaled.fit(X_train_scaled, y_train, epochs=50, batch_size=32, verbose=1)
```

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BUENAFE Assignment 7.1 : Classifications and Regression.ipynb - Colab

```
21/21 [=====] - 0s 2ms/step - loss: 6667321344.0000
Epoch 30/50
21/21 [=====] - 0s 2ms/step - loss: 6540859904.0000
Epoch 31/50
21/21 [=====] - 0s 2ms/step - loss: 6410493952.0000
Epoch 32/50
21/21 [=====] - 0s 2ms/step - loss: 6277344256.0000
Epoch 33/50
21/21 [=====] - 0s 2ms/step - loss: 6130328064.0000
Epoch 34/50
21/21 [=====] - 0s 2ms/step - loss: 5986698752.0000
Epoch 35/50
21/21 [=====] - 0s 2ms/step - loss: 5835498496.0000
Epoch 36/50
21/21 [=====] - 0s 2ms/step - loss: 5683389440.0000
Epoch 37/50
21/21 [=====] - 0s 2ms/step - loss: 5524302336.0000
Epoch 38/50
21/21 [=====] - 0s 2ms/step - loss: 5364847104.0000
Epoch 39/50
21/21 [=====] - 0s 2ms/step - loss: 5202641920.0000
Epoch 40/50
21/21 [=====] - 0s 2ms/step - loss: 5037799424.0000
Epoch 41/50
21/21 [=====] - 0s 2ms/step - loss: 4871534592.0000
Epoch 42/50
21/21 [=====] - 0s 2ms/step - loss: 4706433536.0000
Epoch 43/50
21/21 [=====] - 0s 2ms/step - loss: 4538463232.0000
Epoch 44/50
21/21 [=====] - 0s 2ms/step - loss: 4374000128.0000
Epoch 45/50
21/21 [=====] - 0s 2ms/step - loss: 4210573568.0000
Epoch 46/50
21/21 [=====] - 0s 2ms/step - loss: 4049666304.0000
Epoch 47/50
21/21 [=====] - 0s 2ms/step - loss: 3890202624.0000
Epoch 48/50
21/21 [=====] - 0s 2ms/step - loss: 3735452672.0000
Epoch 49/50
21/21 [=====] - 0s 2ms/step - loss: 3584151040.0000
Epoch 50/50
21/21 [=====] - 0s 2ms/step - loss: 3439695360.0000
<keras.src.callbacks.History at 0x7e9c0e4560e0>
```

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```
# Define a function to create a model with variable number of layers and neurons
def create_model(layers, neurons):
    model = Sequential()
    model.add(Dense(neurons[0], activation='relu', input_dim=X_train_scaled.shape[1]))

    for i in range(1, layers):
        model.add(Dense(neurons[i], activation='relu'))

    model.add(Dense(1, activation='linear'))

    model.compile(loss='mean_squared_error', optimizer='adam')
    return model

# Define the parameters for tuning
layers = [1, 2, 3] # Number of hidden layers
neurons = [32, 64, 128] # Number of neurons in each layer

# Perform grid search to find the best model
best_model = None
best_loss = float('inf')

for layer in layers:
    for neuron in neurons:
        model_tuned = create_model(layer, [neuron] * layer)
        model_tuned.fit(X_train_scaled, y_train, epochs=50, batch_size=32, verbose=0)
        loss = model_tuned.evaluate(X_test_scaled, y_test)

        if loss < best_loss:
            best_loss = loss
            best_model = model_tuned

# Print the best model's architecture and loss
print("Best model architecture:")
best_model.summary()
print("Best model loss:", best_loss)
```

```
6/6 [=====] - 0s 3ms/step - loss: 7910977536.0000
6/6 [=====] - 0s 2ms/step - loss: 7841633280.0000
6/6 [=====] - 0s 3ms/step - loss: 7691759104.0000
6/6 [=====] - 0s 3ms/step - loss: 4316863488.0000
6/6 [=====] - 0s 2ms/step - loss: 1712784384.0000
6/6 [=====] - 0s 3ms/step - loss: 1026023744.0000
6/6 [=====] - 0s 6ms/step - loss: 820184064.0000
6/6 [=====] - 0s 2ms/step - loss: 717905728.0000
6/6 [=====] - 0s 3ms/step - loss: 695052544.0000
```

```
Best model architecture:
Model: "sequential_10"
```

Layer (type)	Output Shape	Param #
=====		
dense_29 (Dense)	(None, 128)	9344
dense_30 (Dense)	(None, 128)	16512
dense_31 (Dense)	(None, 128)	16512
dense_32 (Dense)	(None, 1)	129
=====		
Total params: 42497 (166.00 KB)		