Assignment 2 Task 2

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Step 1: Preprocessing and Data Visualisation

In [ ]:
```
#import libraries
import pandas as pd
import numpy as np
import tensorflow as tf
from tensorflow import keras
```

In [ ]:
```
df = pd.read_csv("magic04.data", header=None)
```

In [ ]:
```
df.head(5)
```

Out [ ]:

	0	1	2	3	4	5	6	7	8	9	10
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.8828	g
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.2610	g
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.7880	g
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.7370	g
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.4620	g

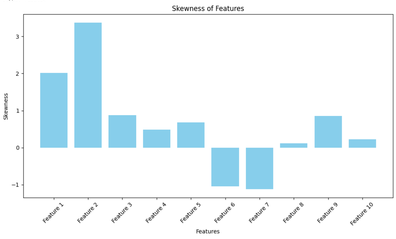
In [ ]:
```
# Calculate skewness of each feature
import pandas as pd
import matplotlib.pyplot as plt
skewness = df.iloc[:, 0:10].skew(axis=0, skipna=True)
print(skewness)


# Create a DataFrame with skewness values and corresponding feature names
features = [f"Feature {i}" for i in range(1, 11)]
data = {'Feature': features, 'Skewness': skewness}
df_skewness = pd.DataFrame(data)

# Create a histogram
plt.figure(figsize=(10, 6))
plt.bar(df_skewness['Feature'], df_skewness['Skewness'], color='skyblue')
plt.xlabel('Features')
plt.ylabel('Skewness')
plt.title('Skewness of Features')
plt.xticks(rotation=45)
plt.tight_layout()

# Show the plot
plt.show()
```

```
0    2.013652
1    3.371628
2    0.875507
3    0.485888
4    0.685695
5   -1.046441
6   -1.123078
7    0.120121
8    0.850899
9    0.229587
dtype: float64
```



Step 2: Pre Processing

In [ ]:
```
X = df.iloc[:, 0:10]
X.head()
```

Out [ ]:

	0	1	2	3	4	5	6	7	8	9
0	28.7967	16.0021	2.6449	0.3918	0.1982	27.7004	22.0110	-8.2027	40.0920	81.8828
1	31.6036	11.7235	2.5185	0.5303	0.3773	26.2722	23.8238	-9.9574	6.3609	205.2610
2	162.0520	136.0310	4.0612	0.0374	0.0187	116.7410	-64.8580	-45.2160	76.9600	256.7880
3	23.8172	9.5728	2.3385	0.6147	0.3922	27.2107	-6.4633	-7.1513	10.4490	116.7370
4	75.1362	30.9205	3.1611	0.3168	0.1832	-5.5277	28.5525	21.8393	4.6480	356.4620

In [ ]:
```
y = df[10]
```

Step 2a: Perform scaling on the data

In [ ]:
```
from sklearn.preprocessing import StandardScaler
scale = StandardScaler()
X = scale.fit_transform(X)

pd.DataFrame(X).describe()
```

Out [ ]:

	0	1	2	3	4	5	6	7	8	9
count	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04	1.902000e+04
mean	-7.172671e-17	-1.195445e-16	-2.241460e-16	-3.025971e-16	1.128201e-16	-5.977226e-18	4.184558e-17	-9.712992e-18	1.195445e-17	-8.965839e-18
std	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00	1.000026e+00
min	-1.155862e+00	-1.209064e+00	-1.869959e+00	-2.008809e+00	-1.930745e+00	-7.661315e+00	-6.712427e+00	-9.897993e+00	-1.059103e+00	-2.576420e+00
25%	-6.825213e-01	-5.623790e-01	-7.361978e-01	-7.905934e-01	-7.798731e-01	-2.745535e-01	-4.586055e-01	-5.329216e-01	-8.465631e-01	-8.868179e-01
50%	-3.800999e-01	-2.747838e-01	-1.807437e-01	-1.431941e-01	-1.643062e-01	1.409487e-01	9.350332e-02	1.999634e-02	-3.818041e-01	-2.631582e-02
75%	3.982656e-01	1.394619e-01	5.852541e-01	6.748758e-01	6.385776e-01	4.796163e-01	4.959385e-01	5.136004e-01	6.986894e-01	6.255307e-01
max	6.631304e+00	1.276608e+01	5.286407e+00	2.804429e+00	4.167515e+00	9.789330e+00	4.466292e+00	8.623528e+00	2.388785e+00	4.037785e+00

Step 2b: Encode Y column (g, h)

In [ ]:
```
# Encode the columns manually
# Change 'g' to 1 and 'h' to 0
y = y.replace('g', 1)
y = y.replace('h', 0)

y.value_counts()
```

Out [ ]:
```
10
1    12332
0     6688
Name: count, dtype: int64
```

Step 2c: Split the data into training and testing sets

In [ ]:
```
from sklearn.model_selection import train_test_split

# Split the data into training and testing sets (2/3 training, 1/3 testing)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33)

# See the shape of the training and testing sets
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("y_train shape:", y_train.shape)
print("y_test shape:", y_test.shape)
```

```
X_train shape: (12743, 10)
X_test shape: (6277, 10)
y_train shape: (12743,)
y_test shape: (6277,)
```

Step 3: Keras Model

In [ ]:
```
from keras.models import Sequential
from keras import layers

# Use ANN to predict gamma or hardon
# Use 2 hidden layers
# Any ANN architecture is allowed

model = Sequential([
    layers.Dense(16, activation='relu', input_shape=(10,)),  # 10 input neurons
    layers.Dense(10, activation='relu'),
    layers.Dense(1, activation='sigmoid')  # 1 output neuron
])

# Compile model
model.compile(optimizer='adam', loss='binary_crossentropy',
              metrics=['accuracy'])
```

In [ ]:
```
# Fit data into model
model_output = model.fit(X_train, y_train, epochs=10,
                         batch_size=10, validation_data=(X_test, y_test))
```

```
Epoch 1/10
1275/1275 [==============================] - 1s 546us/step - loss: 0.4350 - accuracy: 0.7976 - val_loss: 0.3701 - val_accuracy: 0.8397
Epoch 2/10
1275/1275 [==============================] - 1s 475us/step - loss: 0.3588 - accuracy: 0.8500 - val_loss: 0.3470 - val_accuracy: 0.8545
Epoch 3/10
1275/1275 [==============================] - 1s 482us/step - loss: 0.3415 - accuracy: 0.8572 - val_loss: 0.3377 - val_accuracy: 0.8577
Epoch 4/10
1275/1275 [==============================] - 1s 511us/step - loss: 0.3345 - accuracy: 0.8603 - val_loss: 0.3335 - val_accuracy: 0.8657
Epoch 5/10
1275/1275 [==============================] - 1s 491us/step - loss: 0.3292 - accuracy: 0.8625 - val_loss: 0.3242 - val_accuracy: 0.8654
Epoch 6/10
1275/1275 [==============================] - 1s 504us/step - loss: 0.3246 - accuracy: 0.8650 - val_loss: 0.3211 - val_accuracy: 0.8662
Epoch 7/10
1275/1275 [==============================] - 1s 608us/step - loss: 0.3219 - accuracy: 0.8668 - val_loss: 0.3185 - val_accuracy: 0.8668
Epoch 8/10
1275/1275 [==============================] - 1s 516us/step - loss: 0.3202 - accuracy: 0.8678 - val_loss: 0.3201 - val_accuracy: 0.8632
Epoch 9/10
1275/1275 [==============================] - 1s 489us/step - loss: 0.3186 - accuracy: 0.8682 - val_loss: 0.3150 - val_accuracy: 0.8687
Epoch 10/10
1275/1275 [==============================] - 1s 530us/step - loss: 0.3169 - accuracy: 0.8682 - val_loss: 0.3167 - val_accuracy: 0.8678
```

Step 4: Evaluate the model

Step 4a: Evalute the model using the training data

In [ ]:
```
# evaluating and predicting the model
model.evaluate(X_train, y_train)
model.predict(X_train)
```

```
399/399 [==============================] - 0s 301us/step - loss: 0.3137 - accuracy: 0.8694
399/399 [==============================] - 0s 241us/step
```

Out [ ]:
```
array([[0.9870982 ],
       [0.91422385],
       [0.41936665],
       ...,
       [0.826804461,
       [0.62709924],
       [0.9837348 ]], dtype=float32)
```

Step 4b: Evalute the model using the testing data

In [ ]:
```
# evaluating and predicting the model
model.evaluate(X_test, y_test)
model.predict(X_test)
```

```
197/197 [==============================] - 0s 375us/step - loss: 0.3167 - accuracy: 0.8678
197/197 [==============================] - 0s 280us/step
```

Out [ ]:
```
array([[0.80019927],
       [0.9947954 ],
       [0.33353739],
       ...,
       [0.47862267],
       [0.8216229 ],
       [0.8934397]], dtype=float32)
```

Accuracy of Training data: 0.8694

Accuracy of Testing data: 0.8678

Step 5: Hyperparameter Tuning

In [ ]:
```
from scikeras.wrappers import KerasClassifier
from keras.layers import Dense


def create_model(n_hidden=2, n_neurons=16, a=0.01, b=0.01, input_shape=[10]):
    model = Sequential()

    # Input layer
    model.add(keras.layers.Dense(
        n_neurons, activation='relu', input_shape=input_shape))

    # Hidden layers
    for layer in range(n_hidden):
        model.add(keras.layers.Dense(n_neurons, activation='relu',
                                     kernel_regularizer=keras.regularizers.l1_l2(l1=a, l2=b)))

    # Output layer
    model.add(keras.layers.Dense(1))

    model.compile(loss='binary_crossentropy',
                  optimizer='adam', metrics=['accuracy'])
    return model


# Create a KerasRegressor with the build_model function
model_fine_tune = KerasClassifier(model=create_model, verbose=0)
```

In [ ]:
```
# Using GridSearchCV to find the best params for the model
from sklearn.model_selection import GridSearchCV

# Create the parameter grid based on the results of random search
param_grid = {
    'n_hidden': [1, 2, 5],
    'n_neurons': [10, 16, 20],
    'a': [0.1, 0.01],
    'b': [0.1, 0.01]
}
```

In [ ]:
```
model_fine_tune.get_params().keys()
```

Out [ ]:
```
dict_keys(['model', 'build_fn', 'warm_start', 'random_state', 'optimizer', 'loss', 'metrics', 'batch_size', 'validation_batch_size', 'verbose', 'callbacks', 'validation_split', 'shuffle', 'run_eagerly', 'epochs', 'class_weight'])
```

In [ ]:
```
# Create parameter grid that is valid
param_grid = {
    'batch_size': [5, 10, 15],
    'epochs': [50, 100],
    'optimizer': ['adam', 'sgd']
}

# Using GridSearchCV to find the best params for the model
grid = GridSearchCV(estimator=model_fine_tune, param_grid=param_grid, cv=5)
grid_result = grid.fit(X_train, y_train, validation_data=(X_test, y_test))
grid_result.best_params_
grid_result.best_score_
```

Out [ ]:
```
0.8639259524312488
```

In [ ]:
```
print('RESULTS:')
print("Best parameters: %s" % grid_result.best_params_)
print("Best score: %f" % grid_result.best_score_)
print("Best estimator: %s" % grid_result.best_estimator_)
print("Scorer: %s" % grid_result.scorer_)
```

```
RESULTS:
Best parameters: {'batch_size': 15, 'epochs': 100, 'optimizer': 'sgd'}
Best score: 0.863926
Best estimator: KerasClassifier(
    model=<function create_model at 0x281314c10>
    build_fn=None
    warm_start=False
    random_state=None
    optimizer=sgd
    loss=None
    metrics=None
    batch_size=15
    validation_batch_size=None
    verbose=0
    callbacks=None
    validation_split=0.0
    shuffle=True
    run_eagerly=False
    epochs=100
    class_weight=None
)
Scorer: <sklearn.metrics._scorer._PassthroughScorer object at 0x283055840>
```

Step 6: Result Analysis

1. Best parameters for Scikeras' KerasClassifier:

- batch_size: 15
- epochs: 100
- optimizer: sgd This results in best score of 0.863926

2. Difference before fine tuning:

- Accuracy of Training data: 0.8694
- Accuracy of Testing data: 0.8678