

1 **# Comprehensive Assessment : Deep Learning - Predicting Diabetes Progression using Artificial Neural Networks#**

```
In [ ]: 1 #1. Loading and Preprocessing
        2 #Load the Diabetes dataset from sklearn, handle missing values and normalize the features for better performance with the ne
```

```
In [1]: 1 # Import necessary Libraries
        2 from sklearn.datasets import load_diabetes
        3 from sklearn.model_selection import train_test_split
        4 from sklearn.preprocessing import StandardScaler
        5 import numpy as np
        6 import pandas as pd
        7
        8
```

```
In [2]: 1 # Load the dataset
        2 diabetes_data = load_diabetes()
        3
        4
```

```
In [3]: 1 # Convert to a DataFrame for better visualization
        2 data = pd.DataFrame(diabetes_data.data, columns=diabetes_data.feature_names)
        3 target = pd.Series(diabetes_data.target, name='target')
        4
        5
```

```
In [4]: 1 # Check for missing values (if any)
        2 print(data.isnull().sum())
        3
        4
```

```
age      0
sex      0
bmi      0
bp      0
s1      0
s2      0
s3      0
s4      0
s5      0
s6      0
dtype: int64
```

```
In [5]: 1 # Normalize the features using StandardScaler
        2 scaler = StandardScaler()
        3 scaled_data = scaler.fit_transform(data)
        4
        5
```

```
In [6]: 1 # Splitting data into training and test sets (80% train, 20% test)
        2 X_train, X_test, y_train, y_test = train_test_split(scaled_data, target, test_size=0.2, random_state=42)
        3
```

```
In [ ]: 1 #2. Exploratory Data Analysis (EDA)
        2 #perform basic EDA to understand the dataset and visualize relationships between features and the target variable.
```

```
In [7]: 1 # Basic statistics
2 print(data.describe())
3
4
```

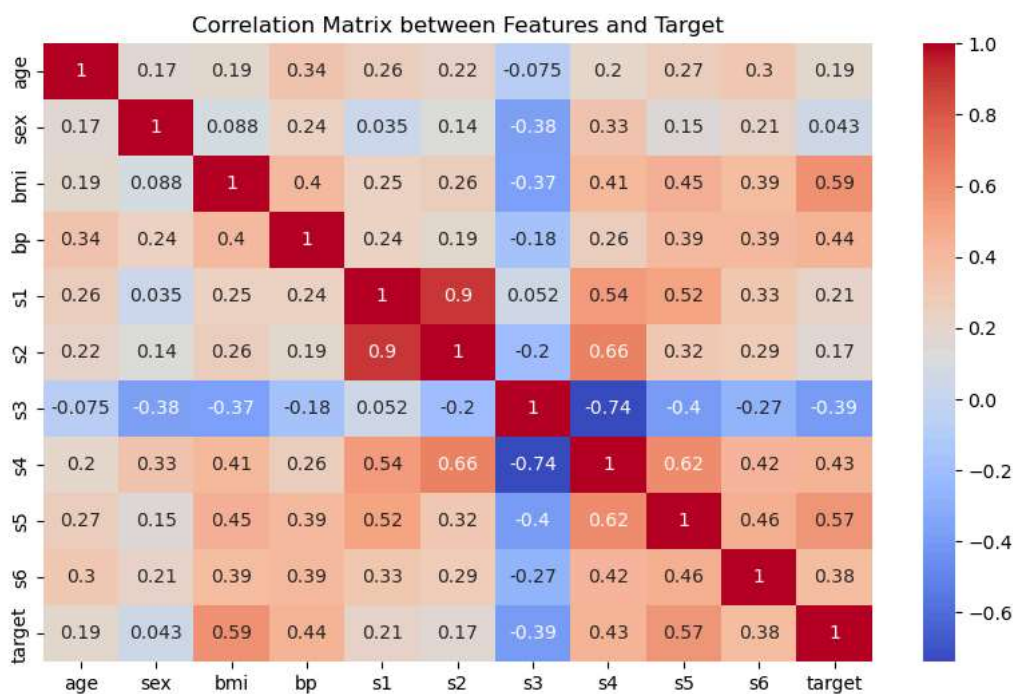
	age	sex	bmi	bp	s1 \
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02
mean	-2.511817e-19	1.230790e-17	-2.245564e-16	-4.797570e-17	-1.381499e-17
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02
min	-1.072256e-01	-4.464164e-02	-9.027530e-02	-1.123988e-01	-1.267807e-01
25%	-3.729927e-02	-4.464164e-02	-3.422907e-02	-3.665608e-02	-3.424784e-02
50%	5.383060e-03	-4.464164e-02	-7.283766e-03	-5.670422e-03	-4.320866e-03
75%	3.807591e-02	5.068012e-02	3.124802e-02	3.564379e-02	2.835801e-02
max	1.107267e-01	5.068012e-02	1.705552e-01	1.320436e-01	1.539137e-01

	s2	s3	s4	s5	s6
count	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02	4.420000e+02
mean	3.918434e-17	-5.777179e-18	-9.042540e-18	9.293722e-17	1.130318e-17
std	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02	4.761905e-02
min	-1.156131e-01	-1.023071e-01	-7.639450e-02	-1.260971e-01	-1.377672e-01
25%	-3.035840e-02	-3.511716e-02	-3.949338e-02	-3.324559e-02	-3.317903e-02
50%	-3.819065e-03	-6.584468e-03	-2.592262e-03	-1.947171e-03	-1.077698e-03
75%	2.984439e-02	2.931150e-02	3.430886e-02	3.243232e-02	2.791705e-02
max	1.987880e-01	1.811791e-01	1.852344e-01	1.335973e-01	1.356118e-01

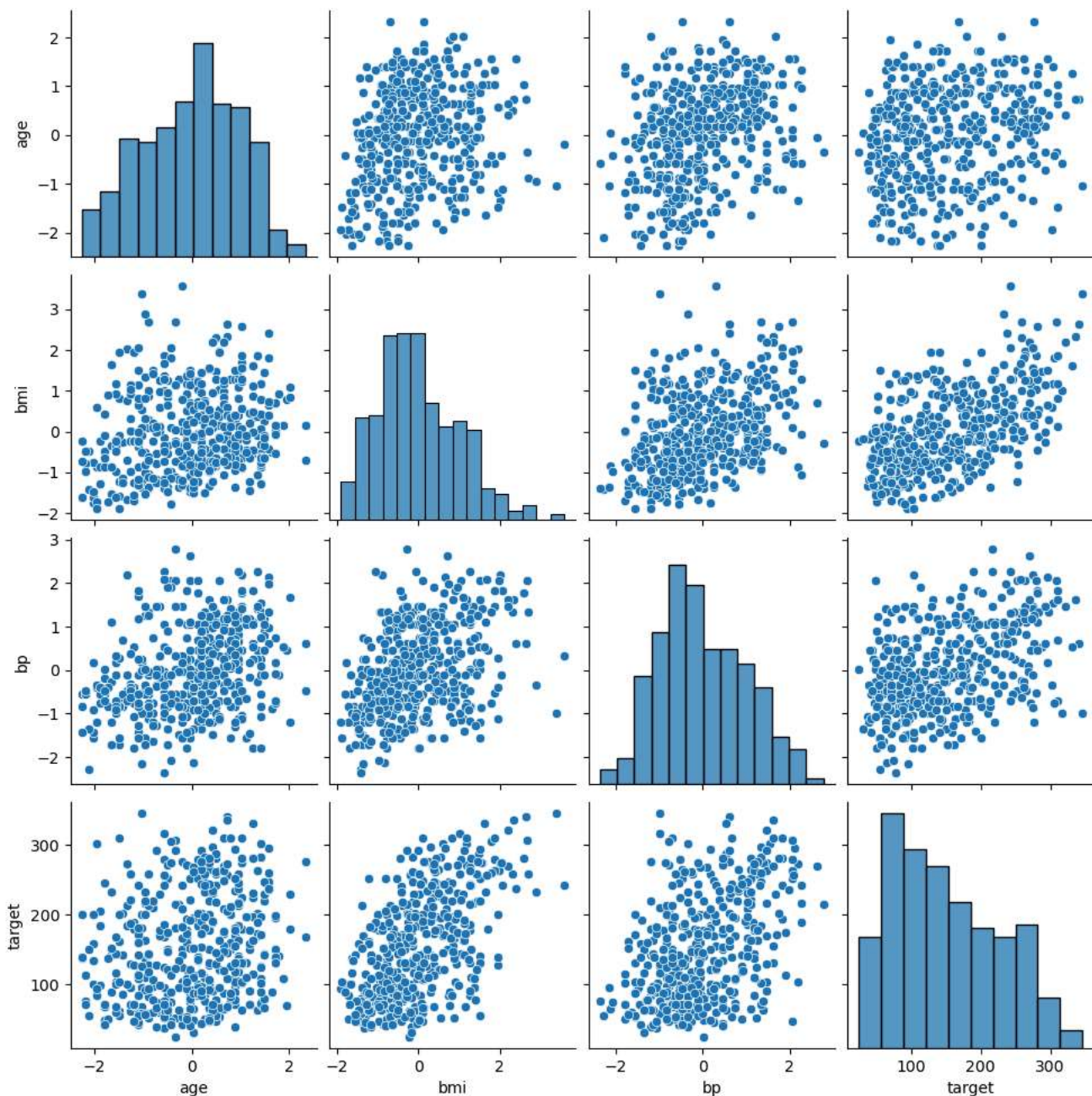
```
In [8]: 1 # Pairplot to understand relationships between features and target
2 import seaborn as sns
3 import matplotlib.pyplot as plt
4
5
```

```
In [9]: 1 # Create a dataframe with scaled data for visualization
2 scaled_df = pd.DataFrame(scaled_data, columns=diabetes_data.feature_names)
3 scaled_df['target'] = target.values
4
5
```

```
In [10]: 1 # Visualize correlations between features and the target
2 plt.figure(figsize=(10, 6))
3 sns.heatmap(scaled_df.corr(), annot=True, cmap='coolwarm')
4 plt.title('Correlation Matrix between Features and Target')
5 plt.show()
6
7
```



```
In [11]: 1 # Scatterplot of some features with target to explore relationships
2 sns.pairplot(scaled_df[['age', 'bmi', 'bp', 'target']])
3 plt.show()
4
```



```
In [ ]: 1 #3. Building the ANN Model
2 #design a simple ANN model using Keras, with at Least one hidden Layer and appropriate activation functions.
```

```
In [12]: 1 # Import necessary libraries for building the ANN
2 import tensorflow as tf
3 from tensorflow.keras.models import Sequential
4 from tensorflow.keras.layers import Dense
5
6
```

```
In [13]: 1 # Build the ANN model
2 model = Sequential()
3
4
```

```
In [14]: 1 # Input Layer and first hidden Layer with ReLU activation
2 model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))
3
4
```

C:\Users\SHONIMA S\AppData\Roaming\Python\Python310\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass a n`input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```
In [15]: 1 # Second hidden Layer
2 model.add(Dense(32, activation='relu'))
3
4
```

```
In [16]: 1 # Output Layer (for regression, no activation)
2 model.add(Dense(1))
3
4
```

```
In [17]: 1 # Compile the model with mean squared error loss function and Adam optimizer
2 model.compile(loss='mean_squared_error', optimizer='adam', metrics=['mse'])
3
```

```
In [ ]: 1 #4. Training the ANN Model
2 #split the dataset into training and testing sets and train the model using the Adam optimizer and mean squared error Loss f
```

```
In [18]: 1 # Train the model
2 history = model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2, verbose=1)
3
```

9/9 ————— 0s 14ms/step - loss: 3328.5027 - mse: 3328.5027 - val_loss: 3038.6499 - val_mse: 3038.6499
Epoch 54/100
9/9 ————— 0s 15ms/step - loss: 3325.8879 - mse: 3325.8879 - val_loss: 3024.3296 - val_mse: 3024.3296
Epoch 55/100
9/9 ————— 0s 13ms/step - loss: 3616.9775 - mse: 3616.9775 - val_loss: 3009.3462 - val_mse: 3009.3462
Epoch 56/100
9/9 ————— 0s 14ms/step - loss: 3207.6099 - mse: 3207.6099 - val_loss: 2995.4495 - val_mse: 2995.4495
Epoch 57/100
9/9 ————— 0s 15ms/step - loss: 3102.1714 - mse: 3102.1714 - val_loss: 2981.8621 - val_mse: 2981.8621
Epoch 58/100
9/9 ————— 0s 15ms/step - loss: 3500.3020 - mse: 3500.3020 - val_loss: 2966.5056 - val_mse: 2966.5056
Epoch 59/100
9/9 ————— 0s 14ms/step - loss: 3149.5830 - mse: 3149.5830 - val_loss: 2959.3887 - val_mse: 2959.3887
Epoch 60/100
9/9 ————— 0s 15ms/step - loss: 3475.3552 - mse: 3475.3552 - val_loss: 2947.0354 - val_mse: 2947.0354
Epoch 61/100
9/9 ————— 0s 15ms/step - loss: 3178.6528 - mse: 3178.6528 - val_loss: 2938.1443 - val_mse: 2938.1443
Epoch 62/100
9/9 ————— 0s 13ms/step - loss: 3084.7791 - mse: 3084.7791 - val_loss: 2926.0896 - val_mse: 2926.0896
Epoch 63/100

```
In [ ]: 1 #5. Evaluating the Model
2 #evaluate the model on the test data and report the performance metrics, such as Mean Squared Error and R² Score.
```

```
In [19]: 1 # Import metrics for evaluation
2 from sklearn.metrics import mean_squared_error, r2_score
3
4
```

```
In [20]: 1 # Predict on test set
2 y_pred = model.predict(X_test)
3
4
```

3/3 ————— 0s 48ms/step

```
In [21]: 1 # Calculate Mean Squared Error and R² Score
2 mse = mean_squared_error(y_test, y_pred)
3 r2 = r2_score(y_test, y_pred)
4
5 print(f'Mean Squared Error: {mse}')
6 print(f'R² Score: {r2}')
7
```

Mean Squared Error: 2889.3804901232
R² Score: 0.4546436894843223

```
In [ ]: 1 #6. Improving the Model
2 #different architectures, such as increasing the number of hidden layers, neurons, or using different activation functions L
```

```
In [22]: 1 # Rebuilding the model with more layers and neurons
2 model_improved = Sequential()
3
4
```

```
In [23]: 1 # Input Layer and first hidden layer with tanh activation
2 model_improved.add(Dense(128, input_dim=X_train.shape[1], activation='tanh'))
3
4
```

C:\Users\SHONIMA S\AppData\Roaming\Python\Python310\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass a n `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```
In [24]: 1 # Second hidden layer with more neurons
2 model_improved.add(Dense(64, activation='tanh'))
3
4
```

```
In [25]: 1 # Third hidden layer
2 model_improved.add(Dense(32, activation='relu'))
3
4
```

```
In [26]: 1 # Output layer
2 model_improved.add(Dense(1))
3
4
```

```
In [27]: 1 # Compile the improved model
2 model_improved.compile(loss='mean_squared_error', optimizer=tf.keras.optimizers.Adam(learning_rate=0.001), metrics=['mse'])
3
4
```

```
In [28]: 1 # Train the improved model
2 history_improved = model_improved.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2, verbose=1)
3
4
```

```
Epoch 1/100
9/9 ————— 3s 61ms/step - loss: 30462.8984 - mse: 30462.8984 - val_loss: 22408.2734 - val_mse: 22408.2734
Epoch 2/100
9/9 ————— 0s 12ms/step - loss: 30698.2129 - mse: 30698.2129 - val_loss: 22238.0391 - val_mse: 22238.0391
Epoch 3/100
9/9 ————— 0s 14ms/step - loss: 31248.4121 - mse: 31248.4121 - val_loss: 22045.9570 - val_mse: 22045.9570
Epoch 4/100
9/9 ————— 0s 15ms/step - loss: 31262.0195 - mse: 31262.0195 - val_loss: 21833.4648 - val_mse: 21833.4648
Epoch 5/100
9/9 ————— 0s 15ms/step - loss: 29341.2539 - mse: 29341.2539 - val_loss: 21590.6133 - val_mse: 21590.6133
Epoch 6/100
9/9 ————— 0s 16ms/step - loss: 27960.4062 - mse: 27960.4062 - val_loss: 21326.8066 - val_mse: 21326.8066
Epoch 7/100
9/9 ————— 0s 15ms/step - loss: 27215.1543 - mse: 27215.1543 - val_loss: 21045.5098 - val_mse: 21045.5098
Epoch 8/100
9/9 ————— 0s 14ms/step - loss: 28403.4883 - mse: 28403.4883 - val_loss: 20734.9473 - val_mse: 20734.9473
Epoch 9/100
9/9 ————— 0s 14ms/step - loss: 29112.6328 - mse: 29112.6328 - val_loss: 20383.4082 - val_mse: 20383.4082
Epoch 10/100
9/9 ————— 0s 14ms/step - loss: 29105.0527 - mse: 29105.0527 - val_loss: 19965.2324 - val_mse: 19965.2324
```

```
In [30]: 1 # Evaluate the improved model
2 y_pred_improved = model_improved.predict(X_test)
3 mse_improved = mean_squared_error(y_test, y_pred_improved)
4 r2_improved = r2_score(y_test, y_pred_improved)
5
6 print(f'Improved Mean Squared Error: {mse_improved}')
7 print(f'Improved R² Score: {r2_improved}')
8
```

```
3/3 ————— 0s 7ms/step
Improved Mean Squared Error: 2759.9279688401743
Improved R² Score: 0.4790772141222813
```

In []:

1