tesile-model

April 25, 2024

1 The tensile Model

1.0.1 Libraries

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1.0.2 Loading the data

[2]:
```python
data = pd.read_csv('Processed_concrete_data.csv')
data.head()
```

[2]:
```
   Samples  Cement amount (g)  Water (g) Type of cement  \
0        1                701        190   WHITE CEMENT
1        2                701        100   WHITE CEMENT
2        3                701        284            OPC
3        4                701        246      KP Silver
4        5                701        277   WHITE CEMENT

   Average Aggregate size (mm)  Aggregate(Coarse)(g)  Aggregate(SAND)(g)  \
0                           20                  2828                1414
1                           10                  2828                1414
2                            5                  2828                1414
3                            5                  2828                1414
4                           20                  2828                1414

   Curing Duration (days)      Admixtures  Load at Fracture (N)  \
0                       7  Air-Entraining                 92776
1                       7  Air-Entraining                 81299
2                       7             NaN                101192
3                       7  Air-Entraining                 55086
4                       7             NaN                 73726

   Tensile Strength (MPa)
0                2.953152
1                2.587828
2                3.221041
```

```
3               1.753442
4               2.346771
```

1.0.3 DATA PROCESSING

[3]:
```
# Summary OF MY DATA
data.describe(include="all").T
```

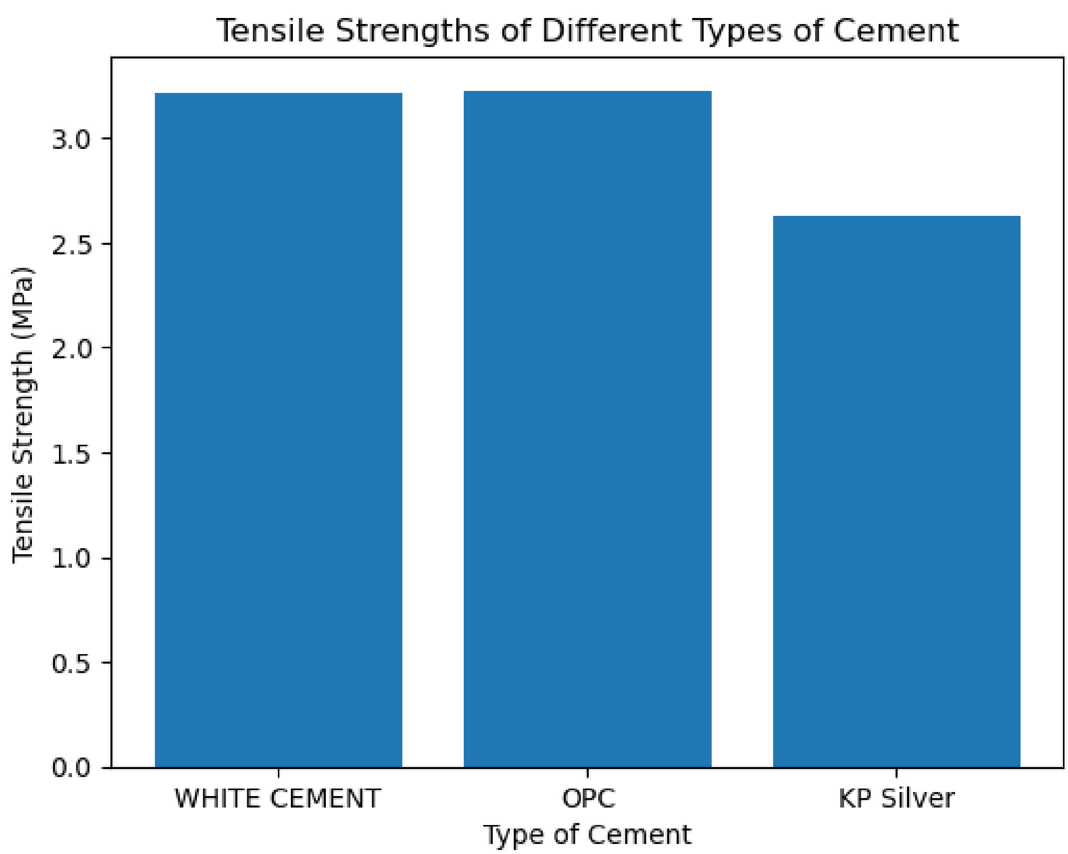
[3]:
```
                             count  unique             top freq          mean  \
Samples                       81.0     NaN             NaN  NaN     13.641975
Cement amount (g)             81.0     NaN             NaN  NaN         701.0
Water (g)                     81.0     NaN             NaN  NaN    321.111111
Type of cement                  81       3   WHITE CEMENT   33           NaN
Average Aggregate size (mm)   81.0     NaN             NaN  NaN     10.679012
Aggregate(Coarse)(g)          81.0     NaN             NaN  NaN        2828.0
Aggregate(SAND)(g)            81.0     NaN             NaN  NaN        1414.0
Curing Duration (days)        81.0     NaN             NaN  NaN           7.0
Admixtures                      38       1  Air-Entraining   38           NaN
Load at Fracture (N)          81.0     NaN             NaN  NaN  76370.925926
Tensile Strength (MPa)        81.0     NaN             NaN  NaN      2.430962

                                       std       min       25%      50%  \
Samples                           7.508843       1.0       8.0     13.0
Cement amount (g)                      0.0     701.0     701.0    701.0
Water (g)                       111.486322     100.0     243.0    334.0
Type of cement                         NaN       NaN       NaN      NaN
Average Aggregate size (mm)       6.111111       5.0       5.0     10.0
Aggregate(Coarse)(g)                   0.0    2828.0    2828.0   2828.0
Aggregate(SAND)(g)                     0.0    1414.0    1414.0   1414.0
Curing Duration (days)                 0.0       7.0       7.0      7.0
Admixtures                             NaN       NaN       NaN      NaN
Load at Fracture (N)          14537.294309   51540.0   63129.0  76112.0
Tensile Strength (MPa)            0.462736  1.640569  2.009458  2.42272

                                  75%       max
Samples                          20.0      27.0
Cement amount (g)               701.0     701.0
Water (g)                       418.0     494.0
Type of cement                    NaN       NaN
Average Aggregate size (mm)      20.0      20.0
Aggregate(Coarse)(g)           2828.0    2828.0
Aggregate(SAND)(g)             1414.0    1414.0
Curing Duration (days)            7.0       7.0
Admixtures                        NaN       NaN
Load at Fracture (N)          89329.0  101329.0
Tensile Strength (MPa)        2.84343  3.225402
```

[4]:
```
data.isnull().sum()
```

[4]:
```
Samples                          0
Cement amount (g)                0
Water (g)                        0
Type of cement                   0
Average Aggregate size (mm)      0
Aggregate(Coarse)(g)             0
Aggregate(SAND)(g)               0
Curing Duration (days)           0
Admixtures                      43
Load at Fracture (N)             0
Tensile Strength (MPa)           0
dtype: int64
```

Check if data is normaly distributed

[5]:
```
plt.bar(data["Type of cement"], data['Tensile Strength (MPa)'])
plt.title('Tensile Strengths of Different Types of Cement')
plt.xlabel('Type of Cement')
plt.ylabel('Tensile Strength (MPa)')
plt.show()
```



1.0.4 Converting the Null values in Admixtures.

If no admixture was used WRITE IT to No Admixture

[6]:
```
data['Admixtures'] = data['Admixtures'].fillna('No Admixture')
data.isnull().sum()
```

[6]:
```
Samples                         0
Cement amount (g)               0
Water (g)                       0
Type of cement                  0
Average Aggregate size (mm)     0
Aggregate(Coarse)(g)            0
Aggregate(SAND)(g)              0
Curing Duration (days)          0
Admixtures                      0
Load at Fracture (N)            0
Tensile Strength (MPa)          0
dtype: int64
```

1.0.5 FEATURE SELECTION

I will do this by removing the columns that I do not need for my model

Like the Samples, Load at Fracture (N)

[7]:
```
data = data.drop(["Samples", "Load at Fracture (N)"], axis=1)
data.head()
```

[7]:
```
   Cement amount (g)  Water (g) Type of cement  Average Aggregate size (mm)  \
0                701        190   WHITE CEMENT                           20
1                701        100   WHITE CEMENT                           10
2                701        284            OPC                            5
3                701        246      KP Silver                            5
4                701        277   WHITE CEMENT                           20

   Aggregate(Coarse)(g)  Aggregate(SAND)(g)  Curing Duration (days)  \
0                  2828                1414                       7
1                  2828                1414                       7
2                  2828                1414                       7
3                  2828                1414                       7
4                  2828                1414                       7

       Admixtures  Tensile Strength (MPa)
0  Air-Entraining                2.953152
1  Air-Entraining                2.587828
```

```
2    No Admixture                3.221041
3  Air-Entraining                1.753442
4    No Admixture                2.346771
```

1.0.6 ENCODING MY COLUMNS

[8]:
```
data.dtypes
```

[8]:
```
Cement amount (g)                int64
Water (g)                        int64
Type of cement                  object
Average Aggregate size (mm)      int64
Aggregate(Coarse)(g)             int64
Aggregate(SAND)(g)               int64
Curing Duration (days)           int64
Admixtures                      object
Tensile Strength (MPa)         float64
dtype: object
```

1.1 Encoding

[9]:
```
data['Type of cement'] = data['Type of cement'].replace({"OPC": 0, "KP Silver":␣
↪1, "WHITE CEMENT": 2})
data['Admixtures'] = data['Admixtures'].replace({"Air-Entraining": 0, "No␣
↪Admixture": 1})
data.head(3)
```

[9]:
```
   Cement amount (g)  Water (g)  Type of cement  Average Aggregate size (mm)  \
0                701        190               2                           20
1                701        100               2                           10
2                701        284               0                            5

   Aggregate(Coarse)(g)  Aggregate(SAND)(g)  Curing Duration (days)  \
0                  2828                1414                       7
1                  2828                1414                       7
2                  2828                1414                       7

   Admixtures  Tensile Strength (MPa)
0           0                2.953152
1           0                2.587828
2           1                3.221041
```

[10]:
```
#data = data.drop(["Cement amount (g)",␣
↪"Aggregate(Coarse)(g)","Aggregate(SAND)(g)","Curing Duration (days)"],␣
↪axis=1)
data.head(3)
```

[10]:

```
   Cement amount (g)  Water (g)  Type of cement  Average Aggregate size (mm)  \
0                701        190               2                           20
1                701        100               2                           10
2                701        284               0                            5

   Aggregate(Coarse)(g)  Aggregate(SAND)(g)  Curing Duration (days)  \
0                  2828                1414                       7
1                  2828                1414                       7
2                  2828                1414                       7

   Admixtures  Tensile Strength (MPa)
0           0                2.953152
1           0                2.587828
2           1                3.221041
```

[11]:

```
data.shape
```

[11]:

```
(81, 9)
```

The data is NOW PERFECT FOR Training my model

2 THE PYTORCH MODEL

[12]:

```
import torch
from torch.utils.data import Dataset, DataLoader
from sklearn.model_selection import train_test_split
from torch import nn, optim
import pandas as pd
```

[13]:

```
from sklearn.preprocessing import StandardScaler
# Assuming df is your DataFrame and that it's already been preprocessed
X = data.drop('Tensile Strength (MPa)', axis=1).values
y = data['Tensile Strength (MPa)'].values

# Initialize a scaler
scaler = StandardScaler()

# Fit on the features and transform
normalized_features = scaler.fit_transform(X)

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

# Convert the data to PyTorch tensors
X_train = torch.FloatTensor(X_train)
y_train = torch.FloatTensor(y_train)
```

```
X_test = torch.FloatTensor(X_test)
y_test = torch.FloatTensor(y_test)
```

2.1 The Model

[14]:
```
import torch
from torch.utils.data import Dataset, DataLoader
from torch import nn, optim

class TensileStrength(nn.Module):
    def __init__(self,input_size,output_size):
        super(TensileStrength, self).__init__()
        self.fc1 = nn.Linear(input_size, 64)
        self.fc2 = nn.Linear(64, 64)
        self.fc3 = nn.Linear(64, 64)
        self.fc4 = nn.Linear(64, 64)
        self.fc5 = nn.Linear(64, output_size)

    def forward(self, x):
        x = torch.relu(self.fc1(x))
        x = torch.relu(self.fc2(x))
        x = torch.relu(self.fc3(x))
        x = torch.relu(self.fc4(x))
        x = self.fc5(x)
        return x
```

[15]:
```
# INITIALIZING THE MODEL
model = TensileStrength(X_train.shape[1], 1)
```

2.1.1 Model Achitecture

[16]:
```
from torchsummary import summary
input_size = (X_train.shape[1],)
summary(model, input_size)
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Linear-1                   [-1, 64]             576
            Linear-2                   [-1, 64]           4,160
            Linear-3                   [-1, 64]           4,160
            Linear-4                   [-1, 64]           4,160
            Linear-5                    [-1, 1]              65
================================================================
Total params: 13,121
Trainable params: 13,121
Non-trainable params: 0
```

```
----------------------------------------------------------------
Input size (MB): 0.00
Forward/backward pass size (MB): 0.00
Params size (MB): 0.05
Estimated Total Size (MB): 0.05
----------------------------------------------------------------
```

2.1.2 LOSS FUNCTION AND MODEL OPTIMIZATION

[17]:
```
criterion = nn.MSELoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.01, weight_decay=0.01)
```

2.2 Training

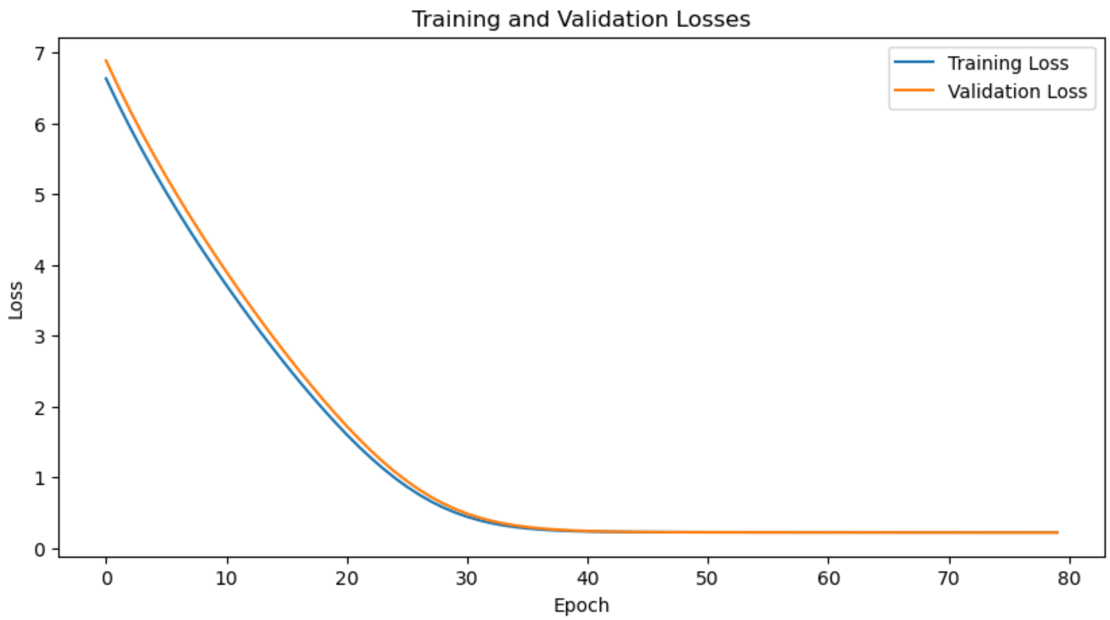
[18]:
```
num_epochs = 80
losses = []  # to store the loss values
val_losses = []  # to store the validation loss values
streak = 0  # to count the streak of constant loss

# Training loop
for epoch in range(num_epochs):
    # Forward pass
    outputs = model(X_train)
    loss = criterion(outputs, y_train)

    # Validate the model
    val_outputs = model(X_test)
    val_loss = criterion(val_outputs, y_test)

    # Backward and optimize
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

    # Save the losses
    losses.append(loss.item())
    val_losses.append(val_loss.item())

    # Check if the loss is constant
    if len(losses) > 1 and losses[-1] == losses[-2]:
        streak += 1
    else:
        streak = 0

    # Stop training if the loss is constant for 10 epochs
    if streak >= 20:
        print('Loss is constant for 10 epochs, stopping training')
```

```
        break

    if (epoch+1) % 100 == 0:
        print ('Epoch [{}/{}], Loss: {:.4f}, Val Loss: {:.4f}'.format(epoch+1,␣
↪num_epochs, loss.item(), val_loss.item()))
```

```
c:\Users\Administrator\anaconda3\Lib\site-packages\torch\nn\modules\loss.py:535:
UserWarning: Using a target size (torch.Size([64])) that is different to the
input size (torch.Size([64, 1])). This will likely lead to incorrect results due
to broadcasting. Please ensure they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
c:\Users\Administrator\anaconda3\Lib\site-packages\torch\nn\modules\loss.py:535:
UserWarning: Using a target size (torch.Size([17])) that is different to the
input size (torch.Size([17, 1])). This will likely lead to incorrect results due
to broadcasting. Please ensure they have the same size.
  return F.mse_loss(input, target, reduction=self.reduction)
```

2.2.1 Loss Vs Epochs

[19]:
```
# Plotting the training and validation loss
plt.figure(figsize=(10,5))
plt.plot(losses, label='Training Loss')
plt.plot(val_losses, label='Validation Loss')
plt.title('Training and Validation Losses')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
plt.show()
```



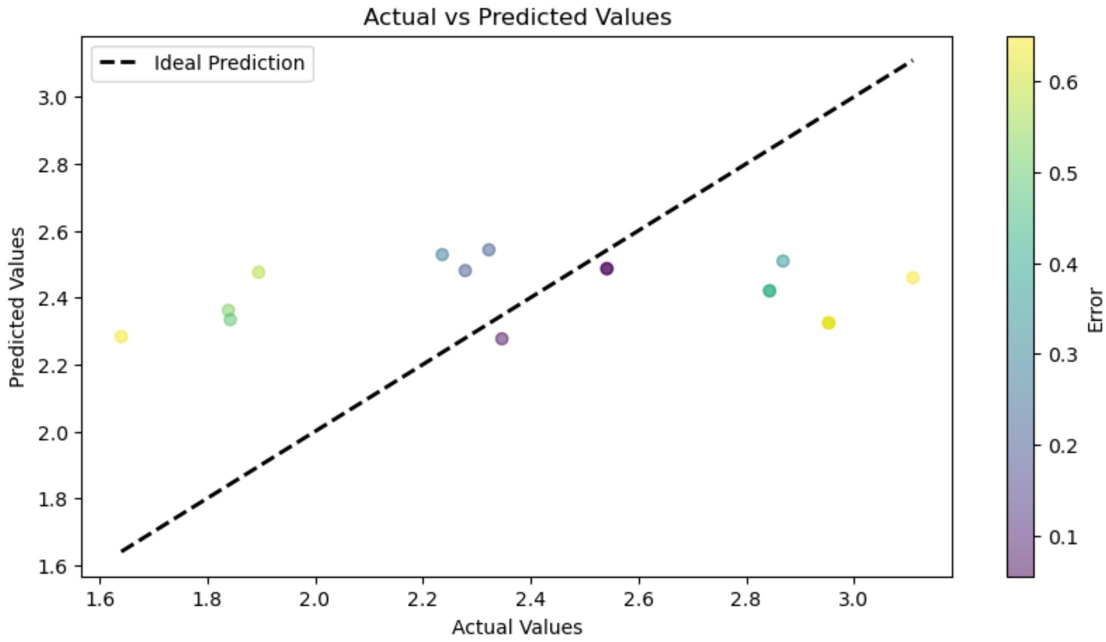
2.2.2 Model evaluation

[20]:
```
# Forward pass on validation data and calculate loss
val_outputs = model(X_test)

# Convert tensors to numpy arrays for plotting
actual_values = y_test.detach().numpy()
predicted_values = val_outputs.detach().numpy()

# Calculate the absolute error
errors = np.abs(actual_values - predicted_values)

print("Shape of actual_values:", actual_values.shape)
print("Shape of predicted_values:", predicted_values.shape)
print("Shape of errors:", errors.shape)
```

```
Shape of actual_values: (17,)
Shape of predicted_values: (17, 1)
Shape of errors: (17, 17)
```

[21]:
```
import matplotlib.pyplot as plt
import numpy as np

# Forward pass on validation data and calculate loss
val_outputs = model(X_test)

# Convert tensors to numpy arrays for plotting
actual_values = y_test.detach().numpy()
predicted_values = np.squeeze(val_outputs.detach().numpy())

# Calculate the absolute error
errors = np.abs(actual_values - predicted_values)

# Create a scatter plot with colors representing the error
plt.figure(figsize=(10,5))
plt.scatter(actual_values, predicted_values, c=errors, cmap='viridis', alpha=0.
 ↪5)
plt.colorbar(label='Error')
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')

# Plot a diagonal line for reference
plt.plot([actual_values.min(), actual_values.max()], [actual_values.min(),␣
 ↪actual_values.max()], 'k--', lw=2, label='Ideal Prediction')
```

```
plt.legend()

plt.show()
```



This scatter plot will help you visualize the correlation between the actual and predicted values. Points that lie on the diagonal line represent perfect predictions, while points that deviate from the line represent errors in prediction.

[22]:
```
from sklearn.metrics import mean_absolute_error, r2_score, mean_squared_error

model.eval()
with torch.no_grad():
    y_pred = model(X_test)

# Convert tensors to numpy arrays for sklearn metrics
y_test_np = y_test.detach().numpy()
y_pred_np = y_pred.detach().numpy()

# Calculate Mean Absolute Error
mae = mean_absolute_error(y_test_np, y_pred_np)
print(f"Mean Absolute Error: {round(mae , 2) } ")

# Calculate Mean Squared Error
mse = mean_squared_error(y_test_np, y_pred_np)
print(f"Mean Squared Error: {round(mse, 2)} ")
```

```
#calculate r2_score error
r2score = r2_score(y_test_np, y_pred_np)
print(f"R-Squared error: {round(r2score*100 , 2)} %")


#R-Squared error: 78.3467 %
```

```
Mean Absolute Error: 0.4000000059604645
Mean Squared Error: 0.20999999344348907
R-Squared error: -1.46 %
```

2.2.3 Save the model

[23]:
```
# Save the model
torch.save(model, 'Model\copytensile_strength_model.pth')
```

prediction

[28]:
```
data = {
    "Cement amount (g)": 701,
    "Water (g)": 500,
    "Type of cement": 2,
    "Aggregate(Coarse)(g)":2828,
    "Aggregate(SAND)(g)": 1414,
    "Average Aggregate size (mm)": 20,
    "Curing Duration (days)": 7,
    "Admixtures":1
}
```

[29]:
```
# Initialize a scaler
scaler = StandardScaler()

# Fit on the features and transform
normalized_features = scaler.fit_transform([list(data.values())])

    # model path
modell = torch.load("Model\copytensile_strength_model.pth")
# Load the state dictionary

# Make a prediction
with torch.no_grad():
    inputs = torch.tensor(normalized_features, dtype=torch.float)
    outputs = modell.forward(inputs)

# Print the data and prediction to the console (optional)
print("Data:", data)
print("Predicted Tensile Strength:", round(outputs.item(), 5), "MPa")
```

```
Data: {'Cement amount (g)': 701, 'Water (g)': 500, 'Type of cement': 2,
'Aggregate(Coarse)(g)': 2828, 'Aggregate(SAND)(g)': 1414, 'Average Aggregate
size (mm)': 20, 'Curing Duration (days)': 7, 'Admixtures': 1}
Predicted Tensile Strength: 2.24014 MPa
```