```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Mounted at /content/gdrive
```

```
import numpy as np
import pandas as pd
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.layers import Dropout
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
```

```
file_name = "/content/gdrive/MyDrive/Colab Notebooks/Yakutsk_weather_19102020_01102012.cs
```

```
df = pd.read_csv(file_name, sep=';',encoding='iso-8859-1')
df.head(10)
```

	LocalTime	T	P0	P	U	DD
0	19.10.2020 17:00	-7.0	745.9	758.2	68.0	Âåòåð
1	19.10.2020 16:30	-6.0	746.0	758.2	63.0	Âåòåð
2	19.10.2020 16:00	-5.0	746.0	758.2	58.0	Âåòåð
3	19.10.2020 15:30	-4.0	746.1	758.2	59.0	Âåòåð
4	19.10.2020 15:00	-4.0	746.1	758.2	54.0	Âåòåð
5	19.10.2020 14:30	-4.0	746.1	758.2	63.0	Âåòåð
6	19.10.2020 14:00	-4.0	746.1	758.2	63.0	Âåòåð
7	19.10.2020 13:30	-4.0	746.1	758.2	63.0	Âåòåð

```
df.drop('DD', axis=1, inplace=True)
df.head(10)
```

	LocalTime	T	P0	P	U
0	19.10.2020 17:00	-7.0	745.9	758.2	68.0
1	19.10.2020 16:30	-6.0	746.0	758.2	63.0
2	19.10.2020 16:00	-5.0	746.0	758.2	58.0
3	19.10.2020 15:30	-4.0	746.1	758.2	59.0

```
df.describe()
```

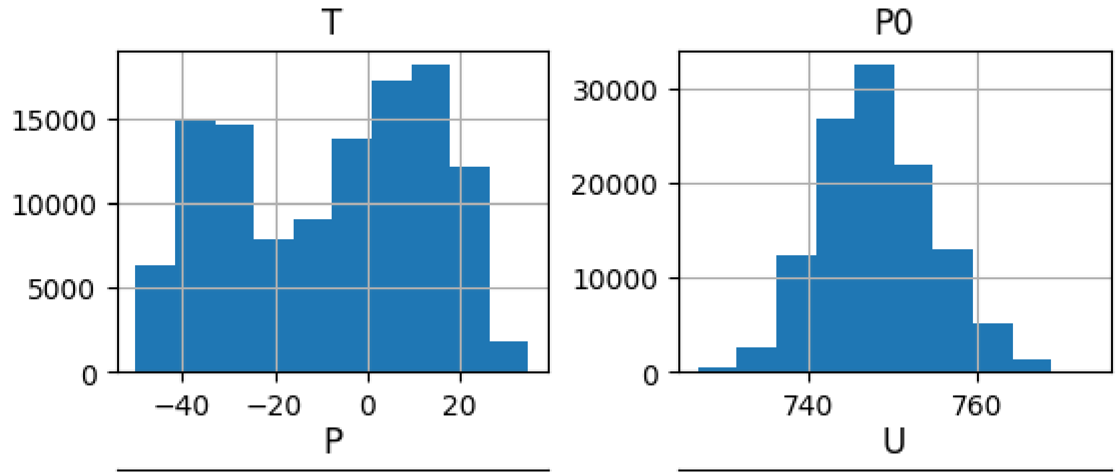
	T	P0	P	U
count	116050.000000	116049.000000	116049.000000	116048.000000
mean	-8.092632	748.080996	760.517001	66.698022
std	21.679891	6.743260	7.464018	17.645702
min	-50.000000	726.800000	738.100000	8.000000
25%	-29.000000	743.400000	755.400000	57.000000
50%	-4.000000	747.700000	759.700000	68.000000
75%	11.000000	752.400000	765.000000	78.000000
max	35.000000	773.400000	787.700000	100.000000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116051 entries, 0 to 116050
Data columns (total 5 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   LocalTime  116051 non-null  object 
 1   T          116050 non-null  float64
 2   P0         116049 non-null  float64
 3   P          116049 non-null  float64
 4   U          116048 non-null  float64
dtypes: float64(4), object(1)
memory usage: 4.4+ MB
```

```
df.hist()
```

```
array([[<Axes: title={'center': 'T'}>, <Axes: title={'center': 'P0'}>],
       [<Axes: title={'center': 'P'}>, <Axes: title={'center': 'U'}>]],
      dtype=object)
```




```
df = df[['LocalTime','T']]
df.head()
```

	LocalTime	T
0	19.10.2020 17:00	-7.0
1	19.10.2020 16:30	-6.0
2	19.10.2020 16:00	-5.0
3	19.10.2020 15:30	-4.0
4	19.10.2020 15:00	-4.0

```
df.isna().sum()
```

```
LocalTime    0
T            1
dtype: int64
```

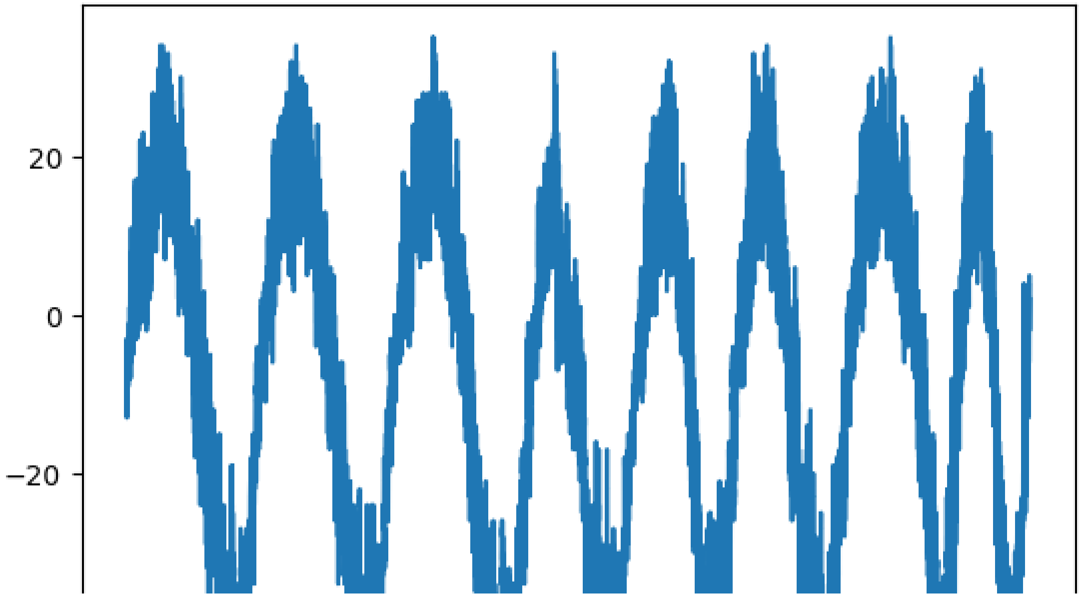
```
df.dropna(inplace=True)
```

```
df.isna().sum()
```

```
LocalTime    0
T            0
dtype: int64
```

```
plt.plot(range(1,len(df['T'].values)+1),df['T'].values)
```

```
[&lt;matplotlib.lines.Line2D at 0x7a5093070760&gt;]
```




```
# Extract and normalize the target column
min_max_scaler = MinMaxScaler()
df = df['T'].values
df = min_max_scaler.fit_transform(df.reshape(-1, 1))
```

```
df.shape
```

```
(116050, 1)
```

```
# Flatten the data shape
df = df.flatten()
df.shape
```

```
(116050,)
```

Split data to train, test, and validation

```
window = 15

# Calculate the number of samples for training, validation, and test sets
n_samples = df.shape[0] - window
n_train_samples = round(0.7 * n_samples)
n_val_samples = round(0.15 * n_samples)
n_test_samples = n_samples - n_train_samples - n_val_samples

print('Train = ',n_train_samples,'Validation = ',n_val_samples,'Test = ',n_test_samples)
```

```
Train =  81224 Validation =  17405 Test =  17406
```

```
# Function to create input-output pairs for a given set
def create_pairs(start_index, num_samples):
    X = [df[start_index + i : start_index + i + window] for i in range(num_samples)]
```

```
    y = [df[start_index + i + window] for i in range(num_samples)]
    return np.array(X), np.array(y)

# Create training, validation, and test sets
X_train, y_train = create_pairs(0, n_train_samples)
X_val, y_val = create_pairs(n_train_samples, n_val_samples)
X_test, y_test = create_pairs(n_train_samples + n_val_samples, n_test_samples)


# Reshape the data
X_train = np.reshape(X_train, (X_train.shape[0], 1, X_train.shape[1]))
X_val = np.reshape(X_val, (X_val.shape[0], 1, X_val.shape[1]))
X_test = np.reshape(X_test, (X_test.shape[0], 1, X_test.shape[1]))
```

Regressor (RNN)

```
# Build the RNN model
rnn_model = tf.keras.Sequential([
    tf.keras.layers.SimpleRNN(10, activation='sigmoid', input_shape=(X_train.shape[1], X_
    Dropout(0.2),
    tf.keras.layers.Dense(1, activation='linear')
])


# Compile the RNN model
rnn_model.compile(loss='mse',
                  optimizer='adam',
                  metrics='mae')


# Train the RNN model
rnn_history = rnn_model.fit(
    X_train,
    y_train,
    epochs=10,
    batch_size=20,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/10
4062/4062 [==============================] - 15s 3ms/step - loss: 0.0359 - mae: 0.13
Epoch 2/10
4062/4062 [==============================] - 12s 3ms/step - loss: 0.0103 - mae: 0.07
Epoch 3/10
4062/4062 [==============================] - 12s 3ms/step - loss: 0.0062 - mae: 0.06
Epoch 4/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0049 - mae: 0.05
Epoch 5/10
4062/4062 [==============================] - 12s 3ms/step - loss: 0.0045 - mae: 0.05
Epoch 6/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0042 - mae: 0.04
Epoch 7/10
4062/4062 [==============================] - 12s 3ms/step - loss: 0.0041 - mae: 0.04
Epoch 8/10
```

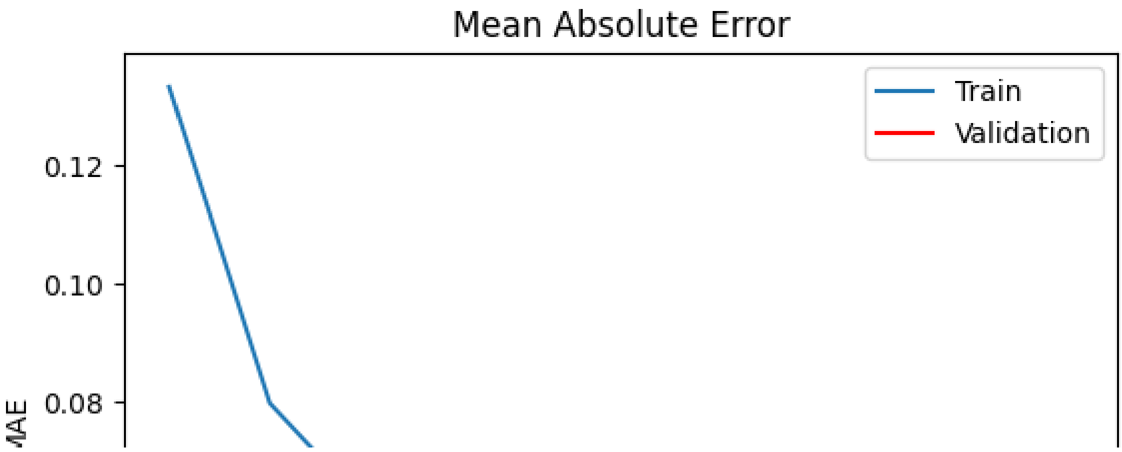
```
4062/4062 [==============================] - 12s 3ms/step - loss: 0.0041 - mae: 0.048
Epoch 9/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0040 - mae: 0.047
Epoch 10/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0040 - mae: 0.047
```

MSE, MAE R2

```
# Get R2, MSE, & MAE scores
y_pred = rnn_model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

r2 = r2_score(y_test, y_pred)

print(f"MSE: {mse:.2f}")
print(f"MAE: {mae:.2f}")
print(f"R-squared (R^2): {r2:.2f}")
```

```
544/544 [==============================] - 1s 2ms/step
MSE: 0.00
MAE: 0.02
R-squared (R^2): 0.99
```

```
# Visualize the mean absolute error
mae = rnn_history.history['mae']
val_mae = rnn_history.history['val_mae']
epochs = range(1,len(mae)+1)

plt.title('Mean Absolute Error')
plt.plot(epochs,mae,label='Train')
plt.plot(epochs,val_mae,color='red',label='Validation')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
```



Predict

```
# Predict using test sets
y_pred = rnn_model.predict(X_test)
y_pred_inv = min_max_scaler.inverse_transform(y_pred)
y_test_inv = min_max_scaler.inverse_transform(y_test.reshape(-1,1))

print('MAE = ',round(mean_absolute_error(y_true=y_test_inv,y_pred=y_pred_inv),3),' degree
print('R2-score = ',round(r2_score(y_test_inv,y_pred_inv),3))
```

```
544/544 [==============================] - 2s 3ms/step
MAE =  2.083  degrees
R2-score =  0.985
```

```
# Visualize prediction
plt.plot(range(1,len(y_test_inv)+1),y_test_inv)
plt.plot(range(1,len(y_pred_inv)+1),y_pred_inv)
```

```
[<matplotlib.lines.Line2D at 0x7a508c162890>]
```

Perpeccop (LSTM)

```
# Build the LSTM model
lstm_model = tf.keras.Sequential([
    tf.keras.layers.LSTM(10, activation='sigmoid', input_shape=(X_train.shape[1], X_trair
    Dropout(0.2),
    tf.keras.layers.Dense(1, activation='relu')
])
```

```
# Compile the LSTM model
lstm_model.compile(loss='mse',
                  optimizer='adam',
                  metrics='mae')
```

```
# Train the LSTM model
lstm_history = lstm_model.fit(
    X_train,
    y_train,
    epochs=10,
    batch_size=20,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/10
4062/4062 [==============================] - 16s 4ms/step - loss: 0.0166 - mae: 0.09
Epoch 2/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0073 - mae: 0.06
Epoch 3/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0051 - mae: 0.05
Epoch 4/10
4062/4062 [==============================] - 13s 3ms/step - loss: 0.0044 - mae: 0.05
Epoch 5/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0041 - mae: 0.04
Epoch 6/10
4062/4062 [==============================] - 15s 4ms/step - loss: 0.0040 - mae: 0.04
Epoch 7/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0039 - mae: 0.04
Epoch 8/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0039 - mae: 0.04
Epoch 9/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0038 - mae: 0.04
Epoch 10/10
4062/4062 [==============================] - 14s 3ms/step - loss: 0.0037 - mae: 0.04
```

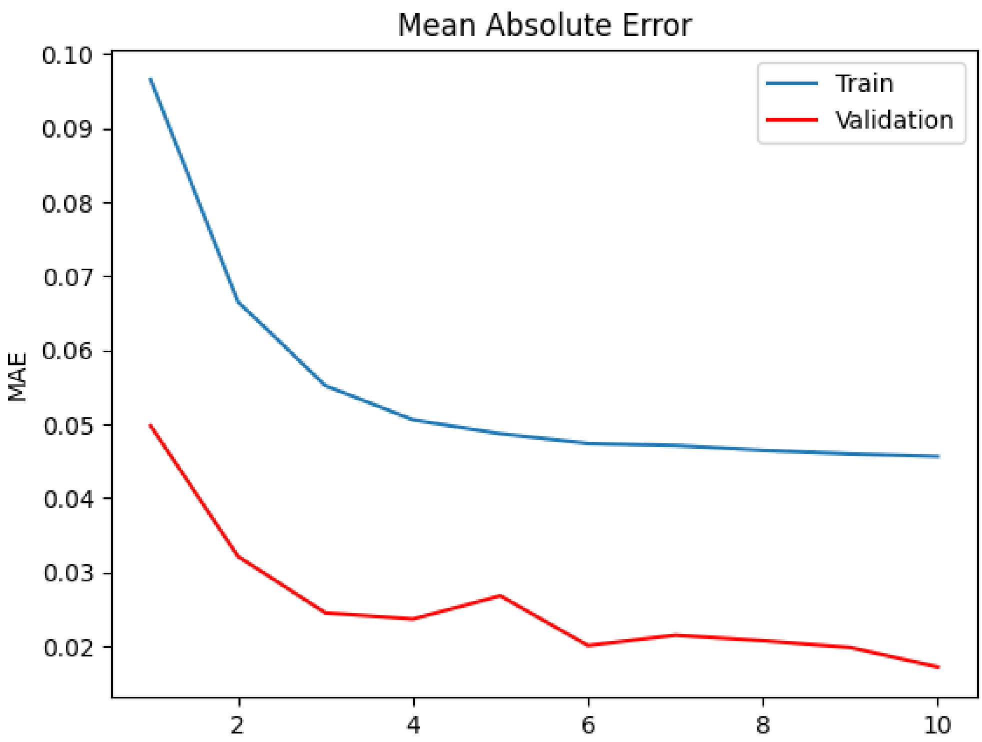
MSE, MAE, R2

```
# Get R2, MSE, & MAE scores
```

```
y_pred = lstm_model.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

r2 = r2_score(y_test, y_pred)

print(f"MSE: {mse:.2f}")
print(f"MAE: {mae:.2f}")
print(f"R-squared (R^2): {r2:.2f}")
```

```
544/544 [==============================] - 1s 2ms/step
MSE: 0.00
MAE: 0.02
R-squared (R^2): 0.99
```

```
# Visualize the mean absolute error
mae = lstm_history.history['mae']
val_mae = lstm_history.history['val_mae']
epochs = range(1,len(mae)+1)

plt.title('Mean Absolute Error')
plt.plot(epochs,mae,label='Train')
plt.plot(epochs,val_mae,color='red',label='Validation')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
```



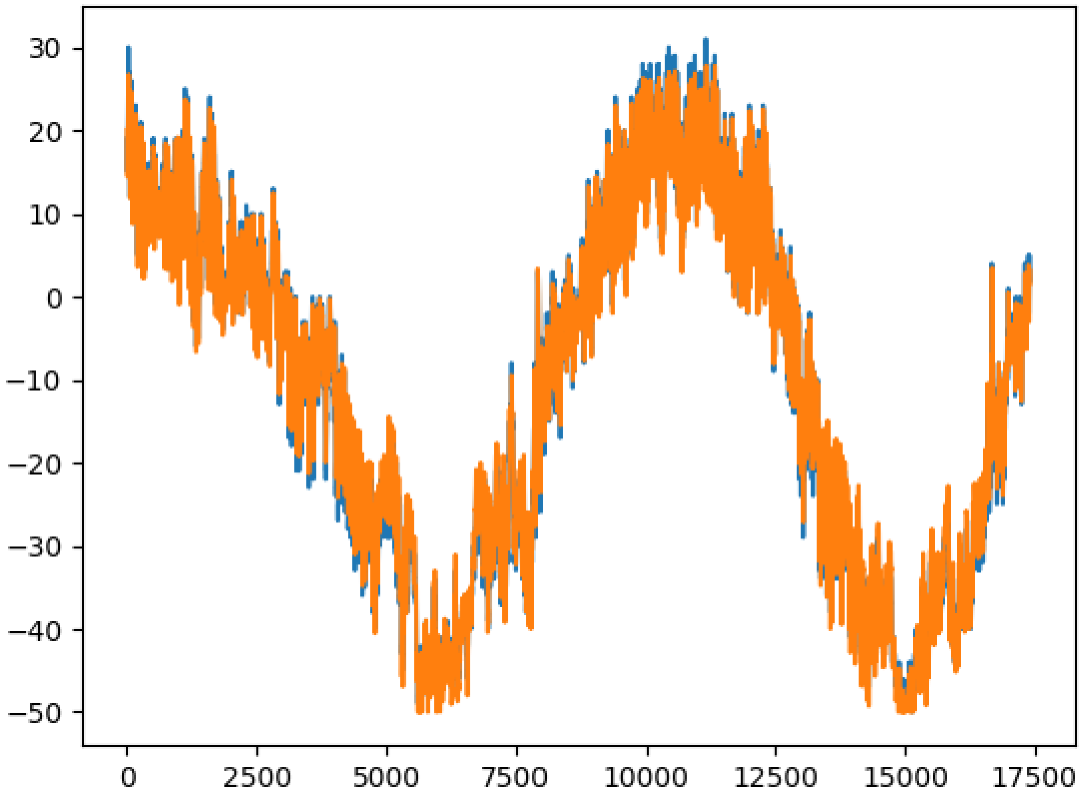
Predict

```
# Predict using test sets
y_pred = lstm_model.predict(X_test)
y_pred_inv = min_max_scaler.inverse_transform(y_pred)
y_test_inv = min_max_scaler.inverse_transform(y_test.reshape(-1,1))

print('MAE = ',round(mean_absolute_error(y_true=y_test_inv,y_pred=y_pred_inv),3),' degree
print('R2-score = ',round(r2_score(y_test_inv,y_pred_inv),3))
```

```
544/544 [==============================] - 1s 2ms/step
MAE =  1.727  degrees
R2-score =  0.989
```

```
# Visualize prediction
plt.plot(range(1,len(y_test_inv)+1),y_test_inv)
plt.plot(range(1,len(y_pred_inv)+1),y_pred_inv)
```

```
[<matplotlib.lines.Line2D at 0x7a507f6bf820>]
```



Regressor (LSTM 2 Layers)

```
# Build the LSTM model
lstm_model2 = tf.keras.Sequential([
    tf.keras.layers.LSTM(10, activation='relu', input_shape=(X_train.shape[1], X_train.sh
    Dropout(0.2),
```

```
    tf.keras.layers.LSTM(10, activation='sigmoid'),
    Dropout(0.2),
    tf.keras.layers.Dense(1, activation='relu')
])


# Compile the LSTM model
lstm_model2.compile(loss='mse',
                  optimizer='adam',
                  metrics='mae')


# Train the LSTM model
lstm_history2 = lstm_model2.fit(
    X_train,
    y_train,
    epochs=20,
    batch_size=20,
    validation_data=(X_val, y_val)
)
```

```
Epoch 1/20
4062/4062 [==============================] - 23s 5ms/step - loss: 0.0353 - mae: 0.133
Epoch 2/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0096 - mae: 0.074
Epoch 3/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0086 - mae: 0.069
Epoch 4/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0080 - mae: 0.066
Epoch 5/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0077 - mae: 0.065
Epoch 6/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0073 - mae: 0.063
Epoch 7/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0073 - mae: 0.062
Epoch 8/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0068 - mae: 0.059
Epoch 9/20
4062/4062 [==============================] - 18s 4ms/step - loss: 0.0066 - mae: 0.058
Epoch 10/20
4062/4062 [==============================] - 18s 4ms/step - loss: 0.0067 - mae: 0.058
Epoch 11/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0065 - mae: 0.057
Epoch 12/20
4062/4062 [==============================] - 20s 5ms/step - loss: 0.0065 - mae: 0.057
Epoch 13/20
4062/4062 [==============================] - 18s 5ms/step - loss: 0.0065 - mae: 0.057
Epoch 14/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0063 - mae: 0.057
Epoch 15/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0064 - mae: 0.057
Epoch 16/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0063 - mae: 0.056
Epoch 17/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0062 - mae: 0.056
Epoch 18/20
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0063 - mae: 0.056
Epoch 19/20
```

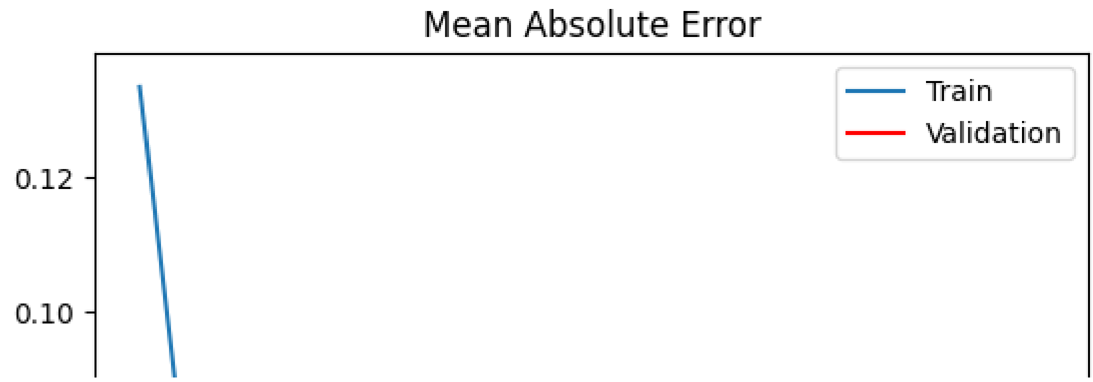
```
4062/4062 [==============================] - 19s 5ms/step - loss: 0.0063 - mae: 0.056
Epoch 20/20
4062/4062 [==============================] - 18s 4ms/step - loss: 0.0062 - mae: 0.056
```

MSE, MAE, R2

```
# Get R2, MSE, & MAE scores
y_pred = lstm_model2.predict(X_test)

mse = mean_squared_error(y_test, y_pred)

mae = mean_absolute_error(y_test, y_pred)

r2 = r2_score(y_test, y_pred)

print(f"MSE: {mse:.2f}")
print(f"MAE: {mae:.2f}")
print(f"R-squared (R^2): {r2:.2f}")
```

```
544/544 [==============================] - 1s 2ms/step
MSE: 0.00
MAE: 0.04
R-squared (R^2): 0.96
```

```
# Visualize the mean absolute error
mae = lstm_history2.history['mae']
val_mae = lstm_history2.history['val_mae']
epochs = range(1,len(mae)+1)

plt.title('Mean Absolute Error')
plt.plot(epochs,mae,label='Train')
plt.plot(epochs,val_mae,color='red',label='Validation')
plt.xlabel('Epochs')
plt.ylabel('MAE')
plt.legend()
plt.show()
```



Predict

```
# Predict using test sets
y_pred = lstm_model2.predict(X_test)
y_pred_inv = min_max_scaler.inverse_transform(y_pred)
y_test_inv = min_max_scaler.inverse_transform(y_test.reshape(-1,1))

print('MAE = ',round(mean_absolute_error(y_true=y_test_inv,y_pred=y_pred_inv),3),' degre
print('R2-score = ',round(r2_score(y_test_inv,y_pred_inv),3))
```

```
544/544 [==============================] - 1s 2ms/step
MAE =  3.323  degrees
R2-score =  0.962
```

```
# Visualize prediction
plt.plot(range(1,len(y_test_inv)+1),y_test_inv)
plt.plot(range(1,len(y_pred_inv)+1),y_pred_inv)
```

```
[<matplotlib.lines.Line2D at 0x7a507f9afe50>]
```