Code and output screenshots from python notebook

 # implementation of LSTM Model to predict the soil temperature for the next 6 months, using Python in jupyter notebook

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 # Subject/Class: CMPS 451 Artificial Intelligence

```
#Step 1:- Import the required libraries
#Numpy for statistical computations
#Matplotlib to plot the graph
#make_blobs from sklearn.datasets
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

#from sklearn.datasets import make_blobs
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
#!pip install tensorflow
import tensorflow as tf

data_path = 'psspredict_new01.csv'

# create pandas dataframe
df = pd.read_csv(data_path)

# remove spaces on the column
df.columns = df.columns.str.lstrip()
df.columns = df.columns.str.rstrip()

# print out sample dataset
print(len(df))
df.head()
```

Out put

```
date  naturaltemperature_5    windspeedscalar   temperature_1p5
      temperature_2      relativehumidity  stationpressure   solarradiation
      windspeed_20f
0     2001/1/2 2:00      0.939 -4.308      4.611 4.599 88.60 4.156 0.335 5.325
1     2001/1/2 3:00      0.950 -4.554      4.283 4.273 52.06 3.964 0.494 5.292
2     2001/1/2 4:00      0.958 -4.513      3.359 3.347 70.40 4.891 0.230 3.822
3     2001/1/2 5:00      0.969 -4.670      3.620 3.606 64.33 4.952 0.276 4.345
4     2001/1/2 6:00      0.976 -5.170      3.819 3.807 62.07 4.699 0.327 4.508
```

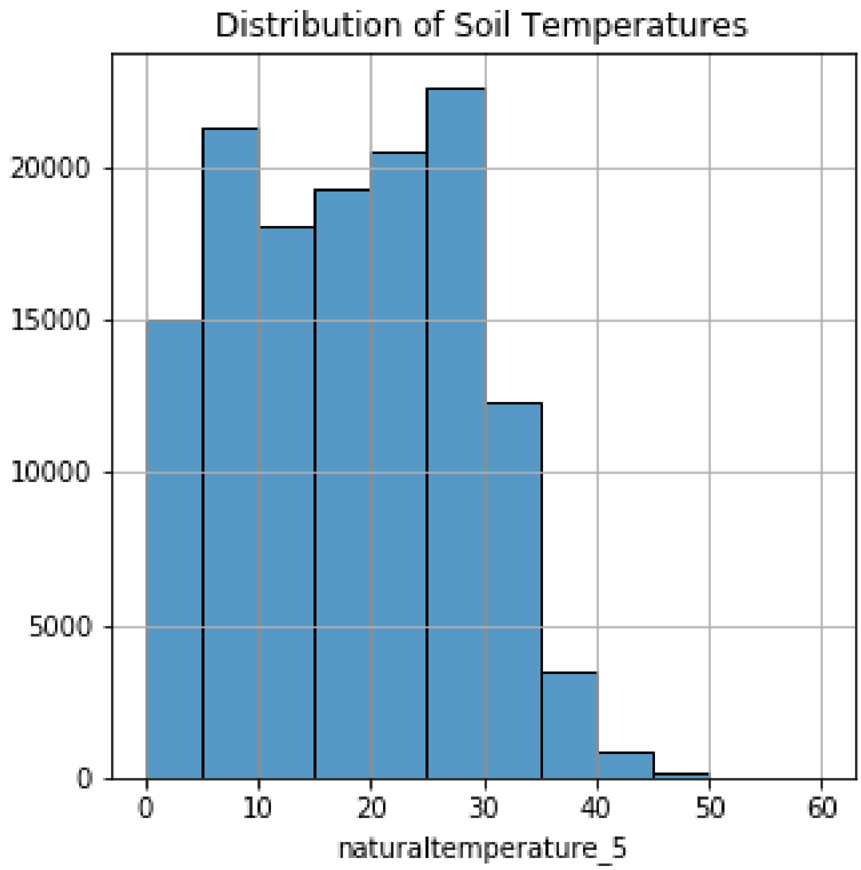
 # check number of nan values in dataframe

df.isna().sum()

Out put

```
date                     0
naturaltemperature_5     0
windspeedscalar          0
temperature_1p5          0
temperature_2            0
relativehumidity         0
stationpressure          0
solarradiation           0
windspeed_20f            0
dtype: int64
```

```
# plot to see the soil temperature varience
#conda update --all
#pip install -U seaborn
plt.figure(figsize=(5, 5))
sns.histplot(df['naturaltemperature_5'],bins=[i for i in range(0,61,5)], kde=False)
plt.title("Distribution of Soil Temperatures")
plt.grid()
#plt.tight_layout()
plt.savefig("SoilTemp2.png")
plt.show()
#sns.histplot(df['windspeedscalar'],bins=[i for i in range(0,61,5)], kde=False)
#plt.title("Distribution of Wind Speed")
#plt.grid()
#plt.show()
```



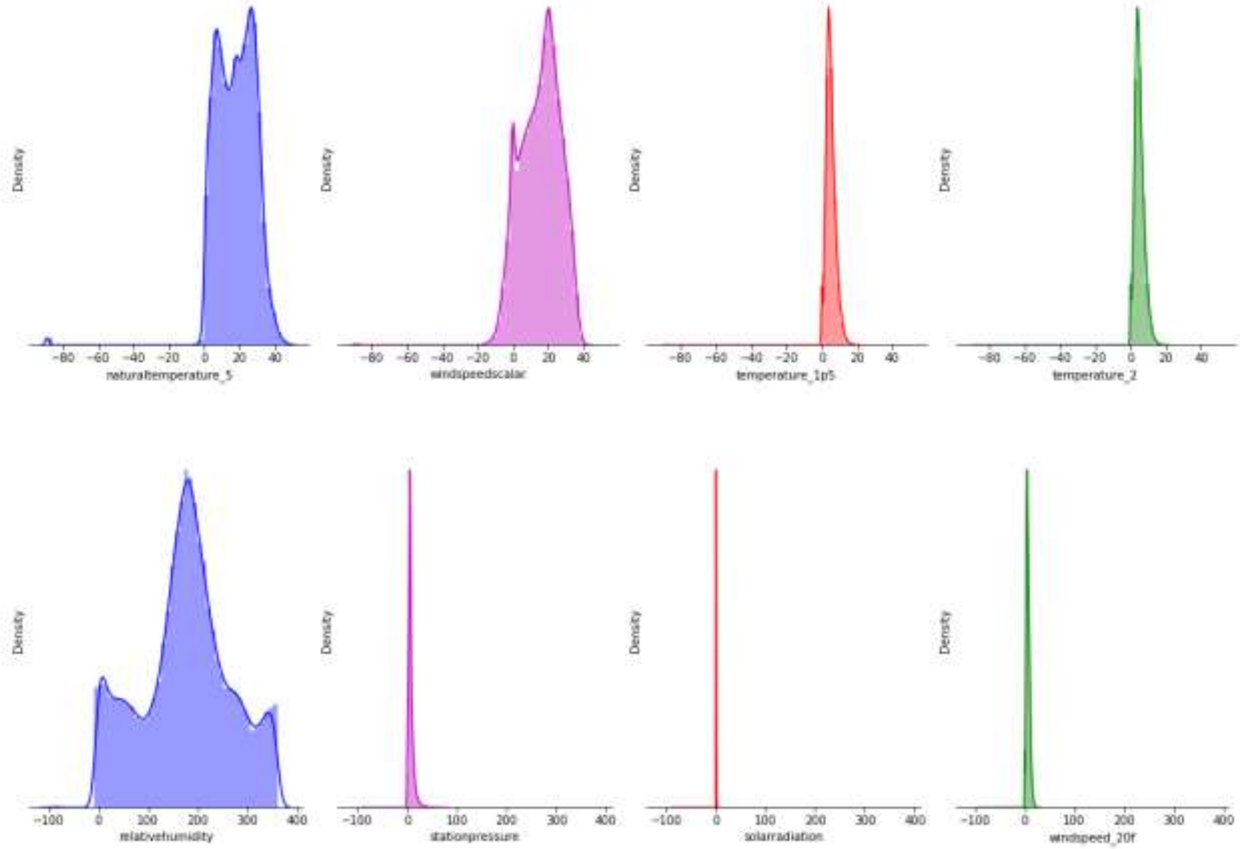

```
f, axes = plt.subplots(2, 4, figsize=(7, 7), sharex=True)

sns.despine(left=True)

# Plot a simple distribution of the desired columns
sns.distplot(df['naturaltemperature_5'], color="b", ax=axes[0, 0])
sns.distplot(df['windspeedscalar'], color="m", ax=axes[0, 1])
sns.distplot(df['temperature_1p5'], color="r", ax=axes[0, 2])
sns.distplot(df['temperature_2'], color="g", ax=axes[0, 3])
sns.distplot(df['relativehumidity'], color="b", ax=axes[1, 0])
sns.distplot(df['stationpressure'], color="m", ax=axes[1, 1])
sns.distplot(df['solarradiation'], color="r", ax=axes[1, 2])
sns.distplot(df['windspeed_20f'], color="g", ax=axes[1, 3])

plt.setp(axes, yticks=[])
plt.tight_layout()
```

#plt.grid()
#plt.show()
plt.savefig("sample.png")



# set data index as datetime column
df.index = pd.to_datetime(df['date'])
# filter the columns by only the required_columns
required_cols = ['naturaltemperature_5', 'windspeedscalar', 'temperature_1p5', 'temperature_2', 'relativehumidity', 'stationpressure', 'solarradiation', 'windspeed_20f']
df = df[required_cols]
df.head()

Out put

```
naturaltemperature_5  windspeedscalar  temperature_1p5  temperature_2
     relativehumidity stationpressure  solarradiation   windspeed_20f
date
2001-01-02 02:00:00    0.939 -4.308      4.611 4.599 88.60 4.156 0.335 5.325
2001-01-02 03:00:00    0.950 -4.554      4.283 4.273 52.06 3.964 0.494 5.292
2001-01-02 04:00:00    0.958 -4.513      3.359 3.347 70.40 4.891 0.230 3.822
```

```
2001-01-02 05:00:00   0.969 -4.670     3.620 3.606 64.33 4.952 0.276 4.345
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```

```
from sklearn.preprocessing import MinMaxScaler

# Normalize the data
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(df)

# Define sequence length and features
sequence_length = 24  # Number of time steps in each sequence
num_features = len(df.columns)

# Create sequences and corresponding labels
sequences = []
labels = []
for i in range(len(scaled_data) - sequence_length):
    seq = scaled_data[i:i+sequence_length]
    label = scaled_data[i+sequence_length][0]  # 'naturaltemperature_5' column index
    sequences.append(seq)
    labels.append(label)

# Convert to numpy arrays
sequences = np.array(sequences)
labels = np.array(labels)

# Split into train and test sets
train_size = int(0.8 * len(sequences))
train_x, test_x = sequences[:train_size], sequences[train_size:]
train_y, test_y = labels[:train_size], labels[train_size:]

print("Train X shape:", train_x.shape)
print("Train Y shape:", train_y.shape)
print("Test X shape:", test_x.shape)
print("Test Y shape:", test_y.shape)
```

```
Train X shape: (105590, 10, 8)
Train Y shape: (105590,)
Test X shape: (26398, 10, 8)
Test Y shape: (26398,)
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint

# Create the LSTM model
model = Sequential()

# Add LSTM layers with dropout
model.add(LSTM(units=128, input_shape=(train_x.shape[1], train_x.shape[2]),
return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=64, return_sequences=True))
model.add(Dropout(0.2))

model.add(LSTM(units=32, return_sequences=False))
model.add(Dropout(0.2))

# Add a dense output layer
model.add(Dense(units=1))

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

model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_3 (LSTM)               (None, 24, 128)           70144

 dropout_3 (Dropout)         (None, 24, 128)           0

 lstm_4 (LSTM)               (None, 24, 64)            49408

 dropout_4 (Dropout)         (None, 24, 64)            0

 lstm_5 (LSTM)               (None, 32)                12416

 dropout_5 (Dropout)         (None, 32)                0

 dense_1 (Dense)             (None, 1)                 33

=================================================================
Total params: 132,001
```

```
Trainable params: 132,001
Non-trainable params: 0
_________________________________________________________________
```

```
# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
model_checkpoint = ModelCheckpoint('C:/Users/Manomay/Downloads/Gargi/CMPS451AI/assignmentsAI/soilTempLSTM/best_model_weights.h5', monitor='val_loss', save_best_only=True)

# Train the model
history = model.fit(
    train_x, train_y,
    epochs=100,
    batch_size=64,
    validation_split=0.2,  # Use part of the training data as validation
    callbacks=[early_stopping, model_checkpoint]
)
```

```
Epoch 1/100
1320/1320 [==============================] - 23s 14ms/step - loss: 0.0075
- val_loss: 8.7919e-04
Epoch 2/100
1320/1320 [==============================] - 19s 15ms/step - loss: 0.0027
- val_loss: 8.0958e-04
Epoch 3/100
1320/1320 [==============================] - 21s 16ms/step - loss: 0.0011
- val_loss: 4.3629e-04
Epoch 4/100
1320/1320 [==============================] - 19s 15ms/step - loss: 4.1244e
-04 - val_loss: 6.4938e-04
Epoch 5/100
1320/1320 [==============================] - 20s 15ms/step - loss: 2.3890e
-04 - val_loss: 6.9732e-04
Epoch 6/100
1320/1320 [==============================] - 19s 14ms/step - loss: 1.8967e
-04 - val_loss: 2.5110e-04
Epoch 7/100
1320/1320 [==============================] - 19s 14ms/step - loss: 1.6482e
-04 - val_loss: 3.1614e-04
Epoch 8/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.6010e
-04 - val_loss: 2.4190e-04
Epoch 9/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.4313e
-04 - val_loss: 2.2215e-04
Epoch 10/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.4497e
-04 - val_loss: 2.2920e-04
```

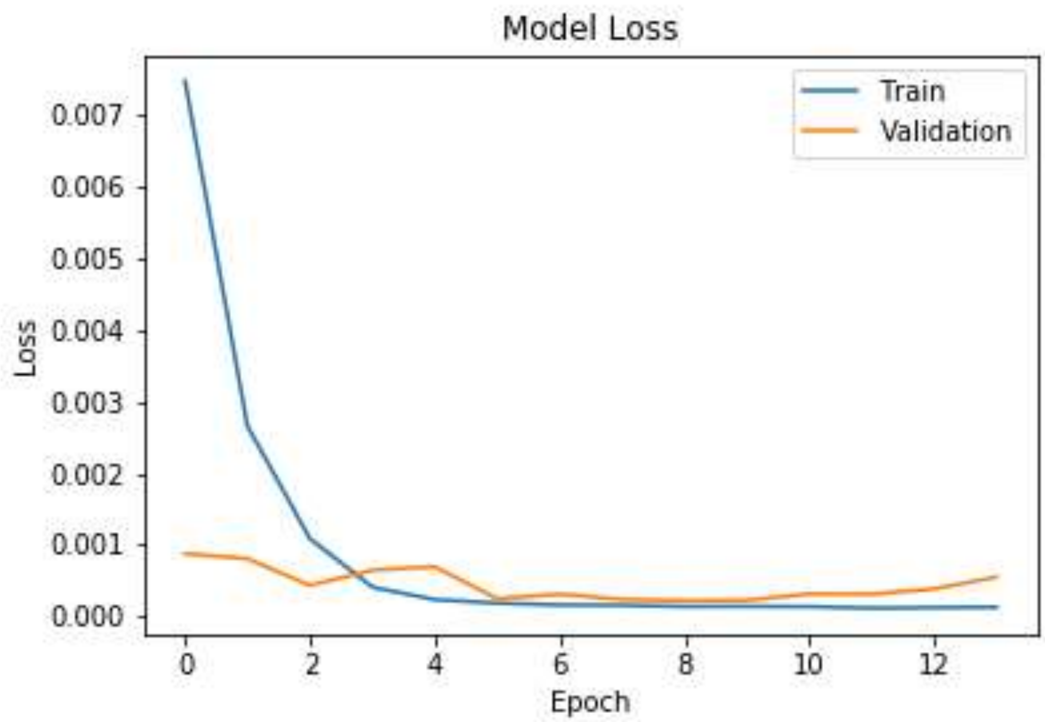
```
Epoch 11/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.4020e
-04 - val_loss: 3.1838e-04
Epoch 12/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.2007e
-04 - val_loss: 3.1465e-04
Epoch 13/100
1320/1320 [==============================] - 19s 15ms/step - loss: 1.2765e
-04 - val_loss: 3.8833e-04
Epoch 14/100
1320/1320 [==============================] - 20s 15ms/step - loss: 1.3454e
-04 - val_loss: 5.5418e-04
Epoch 11/100
1342/1342 [==============================] - 40s 30ms/step - loss: 1.3989e
-04 - val_loss: 2.6575e-04
Epoch 12/100
1342/1342 [==============================] - 40s 30ms/step - loss: 1.2990e
-04 - val_loss: 2.8687e-04
Epoch 13/100
1342/1342 [==============================] - 41s 30ms/step - loss: 1.2928e
-04 - val_loss: 2.4973e-04
Epoch 14/100
1342/1342 [==============================] - 41s 30ms/step - loss: 1.2714e
-04 - val_loss: 2.2059e-04
Epoch 15/100
1342/1342 [==============================] - 41s 30ms/step - loss: 1.2743e
-04 - val_loss: 3.3258e-04
Epoch 16/100
1342/1342 [==============================] - 44s 33ms/step - loss: 1.2538e
-04 - val_loss: 4.1259e-04
Epoch 17/100
1342/1342 [==============================] - 43s 32ms/step - loss: 1.1183e
-04 - val_loss: 5.1869e-04
Epoch 18/100
1342/1342 [==============================] - 42s 32ms/step - loss: 1.0847e
-04 - val_loss: 5.0255e-04
Epoch 19/100
1342/1342 [==============================] - 43s 32ms/step - loss: 1.1605e
-04 - val_loss: 5.3437e-04
```

```
# Evaluate the best model on the test set
best_model = tf.keras.models.load_model('best_model_weights.h5')
test_loss = best_model.evaluate(test_x, test_y)
#provides an estimate of how well the trained model generalizes to new, unseen data
print("Test Loss:", test_loss)
```

```
825/825 [==============================] - 4s 4ms/step - loss: 1.7681e-04
Test Loss: 0.00017681172175798565
```

```
# Plot training & validation loss values
plt.plot(history.history['loss'])
```

```
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper right')
plt.savefig("MLoss.png")
plt.show()
```




```
from sklearn.metrics import mean_absolute_error, mean_squared_error

# Assuming you have trained the model and have the 'best_model' object
# Also, 'test_x' and 'test_y' should be available

# Predict temperatures using the trained model
predictions = best_model.predict(test_x)

# Calculate evaluation metrics
mae = mean_absolute_error(test_y, predictions)
mse = mean_squared_error(test_y, predictions)
rmse = np.sqrt(mse)

print("Mean Absolute Error (MAE):", mae)
print("Mean Squared Error (MSE):", mse)
```

```
print("Root Mean Squared Error (RMSE):", rmse)
```

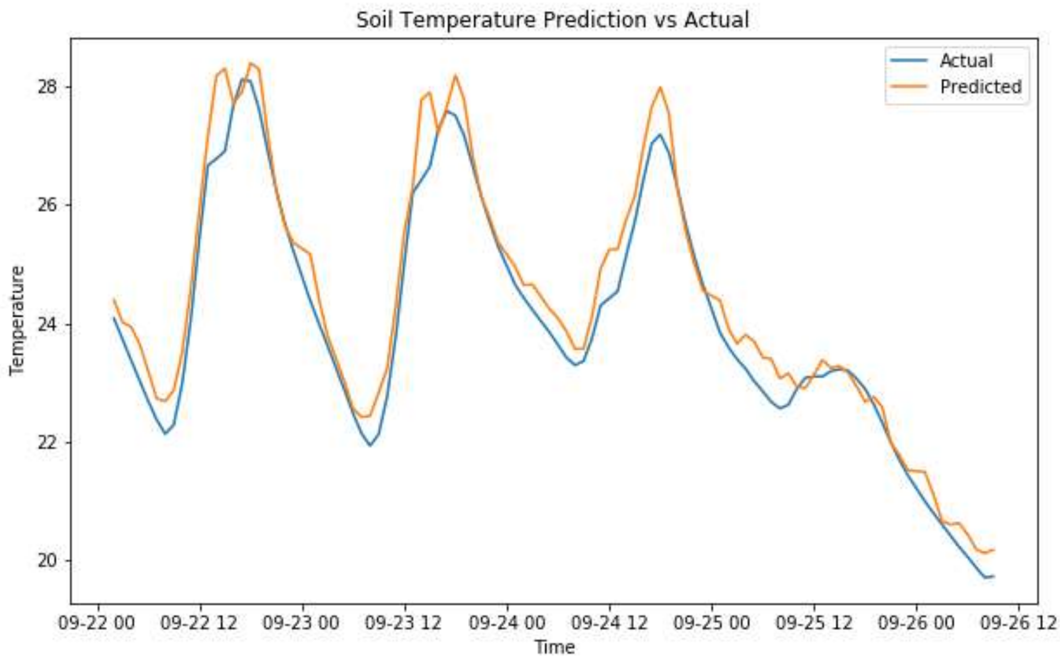
```
825/825 [==============================] - 4s 4ms/step
Mean Absolute Error (MAE): 0.004908275340278715
Mean Squared Error (MSE): 0.00017681170242666888
Root Mean Squared Error (RMSE): 0.013297056156408037
```

```
# y_true values
test_y_copies = np.repeat(test_y.reshape(-1, 1), test_x.shape[-1], axis=-1)
true_temp = scaler.inverse_transform(test_y_copies)[:,0] # 'naturaltemperature_5' column index

# predicted values
prediction = best_model.predict(test_x)
prediction_copies = np.repeat(prediction, num_features, axis=-1)
predicted_temp = scaler.inverse_transform(prediction_copies)[:,0] # 'naturaltemperature_5' column
index
```

```
825/825 [==============================] - 3s 4ms/step
```

```
# Plotting predicted and actual temperatures
plt.figure(figsize=(10, 6))
plt.plot(df.index[-100:], true_temp[-100:], label='Actual')
plt.plot(df.index[-100:], predicted_temp[-100:], label='Predicted')
plt.title('Soil Temperature Prediction vs Actual')
plt.xlabel('Time')
plt.ylabel('Temperature')
plt.legend()
plt.savefig("STempPred.png")
plt.show()
```



Soil Temperature Prediction vs Actual
Actual
Predicted
Temperature
28
26
24
22
20
09-22 00
09-22 12
09-23 00
09-23 12
09-24 00
09-24 12
09-25 00
09-25 12
09-26 00
09-26 12
Time