RNN on Time Series Data

Downloading Jena Climate Dataset

```
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.preprocessing import StandardScaler
```

```
!wget https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
!unzip jena_climate_2009_2016.csv.zip
```

```
--2025-04-03 13:19:47--  https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.217.138.104, 16.15.216.173, 52.217.192.48, ...
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.217.138.104|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 13565642 (13M) [application/zip]
Saving to: ‘jena_climate_2009_2016.csv.zip’

jena_climate_2009_2 100%[===================>]  12.94M  4.65MB/s    in 2.8s

2025-04-03 13:19:51 (4.65 MB/s) - ‘jena_climate_2009_2016.csv.zip’ saved [13565642/13565642]

Archive:  jena_climate_2009_2016.csv.zip
  inflating: jena_climate_2009_2016.csv
  inflating: __MACOSX/._jena_climate_2009_2016.csv
```

```
import os
fname = os.path.join("jena_climate_2009_2016.csv")

with open(fname) as f:
    data = f.read()

lines = data.split("\n")
header = lines[0].split(",")
lines = lines[1:]
print(header)
print(len(lines))
```

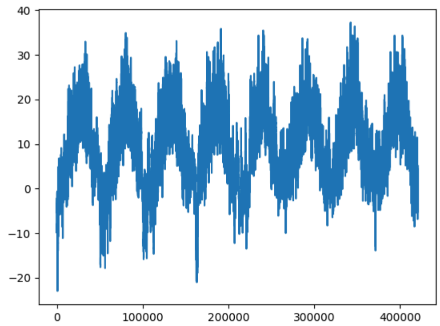
```
['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh (%)"', '"VPmax (mbar)"', '"VPact (mbar)"', '"VPdef (mbar)"', '"sh (g/kg)"', '"H2OC (mmol/mol)"', '"rho (g/m**3)"', '"wv (m/s)"', '"max. wv (m/s)"
420451
```

Preparing Data For Model Building

```
temperature = np.zeros((len(lines),))
raw_data = np.zeros((len(lines), len(header) - 1))
for i, line in enumerate(lines):
    values = [float(x) for x in line.split(",")[1:]]
    temperature[i] = values[1]
    raw_data[i, :] = values[:]
```

```
from matplotlib import pyplot as plt
plt.plot(range(len(temperature)), temperature)
```

```
[<matplotlib.lines.Line2D at 0x78a3551b8b10>]
```




```
print("Temperature Data Shape:", temperature.shape)
print("First 5 Temperature Values:", temperature[:5])

print("Raw Data Shape:", raw_data.shape)
print("First 5 Rows of Raw Data:\n", raw_data[:5])
```

```
Temperature Data Shape: (420451,)
First 5 Temperature Values: [-8.02 -8.41 -8.51 -8.31 -8.27]
Raw Data Shape: (420451, 14)
First 5 Rows of Raw Data:
 [[ 9.96520e+02 -8.02000e+00  2.65400e+02 -8.90000e+00  9.33000e+01
   3.33000e+00  3.11000e+00  2.20000e-01  1.94000e+00  3.12000e+00
   1.30775e+03  1.03000e+00  1.75000e+00  1.52300e+02]
 [ 9.96570e+02 -8.41000e+00  2.65010e+02 -9.28000e+00  9.34000e+01
   3.23000e+00  3.02000e+00  2.10000e-01  1.89000e+00  3.03000e+00
   1.30980e+03  7.20000e-01  1.50000e+00  1.36100e+02]
 [ 9.96530e+02 -8.51000e+00  2.64910e+02 -9.31000e+00  9.39000e+01
   3.21000e+00  3.01000e+00  2.00000e-01  1.88000e+00  3.02000e+00
   1.31024e+03  1.90000e-01  6.30000e-01  1.71600e+02]
 [ 9.96510e+02 -8.31000e+00  2.65120e+02 -9.07000e+00  9.42000e+01
   3.26000e+00  3.07000e+00  1.90000e-01  1.92000e+00  3.08000e+00
   1.30919e+03  3.40000e-01  5.00000e-01  1.98000e+02]
 [ 9.96510e+02 -8.27000e+00  2.65150e+02 -9.04000e+00  9.41000e+01
   3.27000e+00  3.08000e+00  1.90000e-01  1.92000e+00  3.09000e+00
   1.30900e+03  3.20000e-01  6.30000e-01  2.14300e+02]]
```

```
# Normalize features using StandardScaler
scaler = StandardScaler()
normalized_data = scaler.fit_transform(raw_data)
# Setting all the parameters
sampling_rate = 6
sequence_length = 120
delay = sampling_rate * (sequence_length + 24 - 1)
batch_size = 256

# Split data into train (70%), validation (15%), test (15%)
num_train_samples = int(0.7 * (len(normalized_data) - delay))
num_val_samples = int(0.15 * (len(normalized_data) - delay))
num_test_samples = (len(normalized_data) - delay) - (num_train_samples + num_val_samples)

# Create time series datasets
train_dataset = keras.utils.timeseries_dataset_from_array(
    normalized_data[:-delay],  # Use normalized features
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
```

```
    batch_size=batch_size,
    start_index=0,
    end_index=num_train_samples
)

val_dataset = keras.utils.timeseries_dataset_from_array(
    normalized_data[:-delay],  # Use normalized features
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_train_samples,
    end_index=num_train_samples + num_val_samples
)

test_dataset = keras.utils.timeseries_dataset_from_array(
    normalized_data[:-delay],  # Use normalized features
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=False,  # No need to shuffle test data
    batch_size=batch_size,
    start_index=num_train_samples + num_val_samples
)

# Print dataset information
print(f"Train samples: {num_train_samples}")
print(f"Validation samples: {num_val_samples}")
print(f"Test samples: {num_test_samples}")
```

```
Train samples: 293715
Validation samples: 62938
Test samples: 62940
```

1. Building RNN Model

```
# Define the RNN model
model = keras.Sequential([
    layers.SimpleRNN(64, return_sequences=True, input_shape=(sequence_length, normalized_data.shape[1])),
    layers.SimpleRNN(16),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the fi
  super().__init__(**kwargs)
```

Model: "sequential"

Layer (type)	Output Shape	Param #
simple_rnn (SimpleRNN)	(None, 120, 64)	5,056
simple_rnn_1 (SimpleRNN)	(None, 16)	1,296
dense (Dense)	(None, 1)	17

Total params: 6,369 (24.88 KB)
Trainable params: 6,369 (24.88 KB)
Non-trainable params: 0 (0.00 B)

```
# Train the model
history = model.fit(
    train_dataset,
    epochs=20,
    validation_data=val_dataset
)
```

```
Epoch 1/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 47s 41ms/step - loss: 8.0001 - mae: 2.2045 - val_loss: 10.3464 - val_mae: 2.4957
Epoch 2/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 41ms/step - loss: 8.7823 - mae: 2.3166 - val_loss: 10.4396 - val_mae: 2.5073
Epoch 3/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 46s 40ms/step - loss: 8.4120 - mae: 2.2675 - val_loss: 10.6918 - val_mae: 2.5391
Epoch 4/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 86s 43ms/step - loss: 8.0375 - mae: 2.2134 - val_loss: 11.1530 - val_mae: 2.5700
Epoch 5/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 46s 40ms/step - loss: 7.5013 - mae: 2.1388 - val_loss: 11.3324 - val_mae: 2.5954
Epoch 6/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 86s 44ms/step - loss: 7.1449 - mae: 2.0857 - val_loss: 10.9531 - val_mae: 2.5578
Epoch 7/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 43ms/step - loss: 7.9271 - mae: 2.1944 - val_loss: 10.9424 - val_mae: 2.5470
Epoch 8/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 78s 40ms/step - loss: 8.3401 - mae: 2.2532 - val_loss: 11.0392 - val_mae: 2.5707
Epoch 9/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 7.4540 - mae: 2.1322 - val_loss: 10.8795 - val_mae: 2.5455
Epoch 10/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 8.0107 - mae: 2.2075 - val_loss: 10.8949 - val_mae: 2.5606
Epoch 11/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 79s 41ms/step - loss: 7.6722 - mae: 2.1617 - val_loss: 11.4453 - val_mae: 2.6055
Epoch 12/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 7.6383 - mae: 2.1553 - val_loss: 11.9890 - val_mae: 2.6710
Epoch 13/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 42ms/step - loss: 6.9432 - mae: 2.0550 - val_loss: 11.5986 - val_mae: 2.6313
Epoch 14/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 7.2683 - mae: 2.0993 - val_loss: 11.2180 - val_mae: 2.5773
Epoch 15/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 47s 41ms/step - loss: 6.7254 - mae: 2.0282 - val_loss: 11.5997 - val_mae: 2.6282
Epoch 16/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 41ms/step - loss: 6.9122 - mae: 2.0485 - val_loss: 10.7420 - val_mae: 2.5399
Epoch 17/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 42ms/step - loss: 7.5483 - mae: 2.1416 - val_loss: 11.1586 - val_mae: 2.5797
Epoch 18/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 84s 44ms/step - loss: 7.6435 - mae: 2.1494 - val_loss: 10.4746 - val_mae: 2.5066
Epoch 19/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 47s 41ms/step - loss: 8.4334 - mae: 2.2603 - val_loss: 10.7830 - val_mae: 2.5184
Epoch 20/20
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 43ms/step - loss: 8.2406 - mae: 2.2364 - val_loss: 11.0505 - val_mae: 2.5700
```

Adjusting The number of Units for Stacked RNN

```
# Define the improved RNN model
model = keras.Sequential([
    layers.SimpleRNN(64, return_sequences=True, input_shape=(sequence_length, normalized_data.shape[1])),
    layers.SimpleRNN(32, return_sequences=True),
    layers.SimpleRNN(16),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the fi
  super().__init__(**kwargs)
```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
simple_rnn_2 (SimpleRNN)	(None, 120, 64)	5,056
simple_rnn_3 (SimpleRNN)	(None, 120, 32)	3,104
simple_rnn_4 (SimpleRNN)	(None, 16)	784
dense_1 (Dense)	(None, 1)	17

Total params: 8,961 (35.00 KB)
Trainable params: 8,961 (35.00 KB)
Non-trainable params: 0 (0.00 B)

```
# Train the model
history = model.fit(
    train_dataset,
    epochs=30,  # Increased epochs for better learning
    validation_data=val_dataset
)
```

```
Epoch 2/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 11.7837 - mae: 2.5989 - val_loss: 11.8636 - val_mae: 2.6327
Epoch 3/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 10.5153 - mae: 2.5170 - val_loss: 10.6655 - val_mae: 2.5220
Epoch 4/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 42ms/step - loss: 9.8305 - mae: 2.4399 - val_loss: 10.3715 - val_mae: 2.4837
Epoch 5/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 9.4927 - mae: 2.3983 - val_loss: 10.9828 - val_mae: 2.5595
Epoch 6/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 9.4448 - mae: 2.3936 - val_loss: 10.2837 - val_mae: 2.4738
Epoch 7/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 9.1271 - mae: 2.3509 - val_loss: 10.5365 - val_mae: 2.5191
Epoch 8/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 9.0076 - mae: 2.3357 - val_loss: 10.7726 - val_mae: 2.5441
Epoch 9/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 9.5145 - mae: 2.4086 - val_loss: 10.4468 - val_mae: 2.5043
Epoch 10/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 84s 46ms/step - loss: 8.9993 - mae: 2.3384 - val_loss: 10.2237 - val_mae: 2.4820
Epoch 11/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 8.7504 - mae: 2.3103 - val_loss: 10.1814 - val_mae: 2.4743
Epoch 12/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 8.5224 - mae: 2.2798 - val_loss: 10.3304 - val_mae: 2.4782
Epoch 13/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 8.5586 - mae: 2.2856 - val_loss: 10.4098 - val_mae: 2.5191
Epoch 14/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 8.0469 - mae: 2.2164 - val_loss: 11.0829 - val_mae: 2.5875
Epoch 15/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 81s 43ms/step - loss: 7.7795 - mae: 2.1773 - val_loss: 10.7972 - val_mae: 2.5637
Epoch 16/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 42ms/step - loss: 7.6930 - mae: 2.1635 - val_loss: 10.8107 - val_mae: 2.5491
Epoch 17/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 7.6396 - mae: 2.1525 - val_loss: 10.7558 - val_mae: 2.5459
Epoch 18/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 7.2092 - mae: 2.0931 - val_loss: 11.2182 - val_mae: 2.5931
Epoch 19/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 6.8877 - mae: 2.0446 - val_loss: 11.2603 - val_mae: 2.6102
Epoch 20/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 43ms/step - loss: 6.3583 - mae: 1.9636 - val_loss: 11.3173 - val_mae: 2.5994
Epoch 21/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 6.0659 - mae: 1.9177 - val_loss: 11.7530 - val_mae: 2.6496
Epoch 22/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 43ms/step - loss: 6.0259 - mae: 1.9120 - val_loss: 11.8512 - val_mae: 2.6794
Epoch 23/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 43ms/step - loss: 5.7074 - mae: 1.8593 - val_loss: 11.4545 - val_mae: 2.6017
Epoch 24/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 42ms/step - loss: 8.2114 - mae: 2.2263 - val_loss: 11.9153 - val_mae: 2.6810
Epoch 25/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 42ms/step - loss: 5.4051 - mae: 1.8114 - val_loss: 12.3723 - val_mae: 2.7444
Epoch 26/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 43ms/step - loss: 5.0972 - mae: 1.7596 - val_loss: 12.1679 - val_mae: 2.6891
Epoch 27/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 43ms/step - loss: 5.3705 - mae: 1.7989 - val_loss: 12.1267 - val_mae: 2.7111
Epoch 28/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 43ms/step - loss: 4.9201 - mae: 1.7256 - val_loss: 12.6331 - val_mae: 2.7469
Epoch 29/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 6.1998 - mae: 1.9184 - val_loss: 11.3199 - val_mae: 2.6009
Epoch 30/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 52s 45ms/step - loss: 7.4081 - mae: 2.1124 - val_loss: 11.7214 - val_mae: 2.6263
```

Model using GRU

```
# Define the GRU model
model_gru = keras.Sequential([
    layers.GRU(64, return_sequences=True, input_shape=(sequence_length, normalized_data.shape[1])),
    layers.GRU(32, return_sequences=True),
    layers.GRU(16),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model_gru.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model_gru.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
gru (GRU)	(None, 120, 64)	15,360
gru_1 (GRU)	(None, 120, 32)	9,408
gru_2 (GRU)	(None, 16)	2,400
dense_2 (Dense)	(None, 1)	17

Total params: 27,185 (106.19 KB)
Trainable params: 27,185 (106.19 KB)
Non-trainable params: 0 (0.00 B)

```
# Train the model
history_gru = model_gru.fit(
    train_dataset,
    epochs=30,  # Same as LSTM for comparison
    validation_data=val_dataset
)
```

```
Epoch 2/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 10.5862 - mae: 2.4210 - val_loss: 12.5172 - val_mae: 2.7207
Epoch 3/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 48ms/step - loss: 5.8645 - mae: 1.8403 - val_loss: 13.1166 - val_mae: 2.8252
Epoch 4/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 79s 46ms/step - loss: 3.7873 - mae: 1.4840 - val_loss: 13.2117 - val_mae: 2.8620
Epoch 5/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 49ms/step - loss: 2.7636 - mae: 1.2742 - val_loss: 13.8203 - val_mae: 2.9314
Epoch 6/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 2.1966 - mae: 1.1429 - val_loss: 14.4307 - val_mae: 3.0008
Epoch 7/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 49ms/step - loss: 1.8224 - mae: 1.0444 - val_loss: 14.8544 - val_mae: 3.0393
Epoch 8/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 80s 47ms/step - loss: 1.5887 - mae: 0.9752 - val_loss: 15.3161 - val_mae: 3.0751
Epoch 9/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 1.4146 - mae: 0.9205 - val_loss: 14.9728 - val_mae: 3.0299
Epoch 10/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 55s 48ms/step - loss: 1.2845 - mae: 0.8777 - val_loss: 14.8499 - val_mae: 3.0279
```

```
Epoch 12/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 57s 49ms/step - loss: 1.0817 - mae: 0.8055 - val_loss: 15.0993 - val_mae: 3.0282
Epoch 13/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 1.0204 - mae: 0.7811 - val_loss: 14.8671 - val_mae: 3.0041
Epoch 14/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.9587 - mae: 0.7568 - val_loss: 14.7760 - val_mae: 2.9953
Epoch 15/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.9071 - mae: 0.7358 - val_loss: 14.5246 - val_mae: 2.9795
Epoch 16/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.8600 - mae: 0.7174 - val_loss: 14.6979 - val_mae: 2.9885
Epoch 17/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 57s 49ms/step - loss: 0.8196 - mae: 0.6992 - val_loss: 14.8189 - val_mae: 3.0043
Epoch 18/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.7999 - mae: 0.6902 - val_loss: 14.4600 - val_mae: 2.9584
Epoch 19/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.7677 - mae: 0.6755 - val_loss: 14.6125 - val_mae: 2.9851
Epoch 20/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 84s 47ms/step - loss: 0.7437 - mae: 0.6646 - val_loss: 14.4007 - val_mae: 2.9529
Epoch 21/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 49ms/step - loss: 0.7071 - mae: 0.6476 - val_loss: 14.5491 - val_mae: 2.9764
Epoch 22/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 78s 46ms/step - loss: 0.6949 - mae: 0.6427 - val_loss: 14.5765 - val_mae: 2.9703
Epoch 23/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 47ms/step - loss: 0.6740 - mae: 0.6317 - val_loss: 14.4881 - val_mae: 2.9611
Epoch 24/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 52s 45ms/step - loss: 0.6564 - mae: 0.6238 - val_loss: 14.3511 - val_mae: 2.9578
Epoch 25/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 45ms/step - loss: 0.6280 - mae: 0.6101 - val_loss: 14.5658 - val_mae: 2.9692
Epoch 26/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 49ms/step - loss: 0.6285 - mae: 0.6102 - val_loss: 14.3562 - val_mae: 2.9566
Epoch 27/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 47ms/step - loss: 0.6092 - mae: 0.6002 - val_loss: 14.4354 - val_mae: 2.9681
Epoch 28/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.5947 - mae: 0.5929 - val_loss: 14.6317 - val_mae: 2.9810
Epoch 29/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.5901 - mae: 0.5904 - val_loss: 14.4601 - val_mae: 2.9617
Epoch 30/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.5749 - mae: 0.5830 - val_loss: 14.2534 - val_mae: 2.9517
```

2. Using LSTM Layers instead of GRU

```
# Define the LSTM model
model_lstm = keras.Sequential([
    layers.LSTM(64, return_sequences=True, input_shape=(sequence_length, normalized_data.shape[1])),
    layers.LSTM(32, return_sequences=True),
    layers.LSTM(16),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model_lstm.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model_lstm.summary()
```

Model: "sequential_3"

Layer (type)	Output Shape	Param #
lstm (LSTM)	(None, 120, 64)	20,224
lstm_1 (LSTM)	(None, 120, 32)	12,416
lstm_2 (LSTM)	(None, 16)	3,136
dense_3 (Dense)	(None, 1)	17

Total params: 35,793 (139.82 KB)
Trainable params: 35,793 (139.82 KB)
Non-trainable params: 0 (0.00 B)

```
# Train the model
history_lstm = model_lstm.fit(
    train_dataset,
    epochs=30,  # Increased epochs for better learning
    validation_data=val_dataset
)
```

```
Epoch 2/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 9.6826 - mae: 2.2367 - val_loss: 13.3410 - val_mae: 2.8229
Epoch 3/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 55s 48ms/step - loss: 5.1259 - mae: 1.6494 - val_loss: 13.2444 - val_mae: 2.8525
Epoch 4/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 80s 46ms/step - loss: 3.4147 - mae: 1.3519 - val_loss: 13.3806 - val_mae: 2.8799
Epoch 5/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 2.5847 - mae: 1.1861 - val_loss: 13.6986 - val_mae: 2.9097
Epoch 6/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 48ms/step - loss: 2.4446 - mae: 1.1617 - val_loss: 13.3372 - val_mae: 2.8857
Epoch 7/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 1.6958 - mae: 0.9809 - val_loss: 14.0675 - val_mae: 2.9627
Epoch 8/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 1.4346 - mae: 0.9025 - val_loss: 14.7970 - val_mae: 3.0369
Epoch 9/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 47ms/step - loss: 1.2717 - mae: 0.8515 - val_loss: 14.9297 - val_mae: 3.0465
Epoch 10/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 85s 49ms/step - loss: 1.1558 - mae: 0.8124 - val_loss: 14.6274 - val_mae: 3.0227
Epoch 11/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 80s 47ms/step - loss: 1.0715 - mae: 0.7828 - val_loss: 14.6894 - val_mae: 3.0467
Epoch 12/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 57s 49ms/step - loss: 0.9915 - mae: 0.7522 - val_loss: 15.1813 - val_mae: 3.0908
Epoch 13/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.9016 - mae: 0.7184 - val_loss: 15.2459 - val_mae: 3.0836
Epoch 14/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 55s 48ms/step - loss: 0.8612 - mae: 0.7023 - val_loss: 14.7995 - val_mae: 3.0405
Epoch 15/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.8259 - mae: 0.6868 - val_loss: 15.0041 - val_mae: 3.0642
Epoch 16/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.8534 - mae: 0.6909 - val_loss: 14.9544 - val_mae: 3.0527
Epoch 17/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.7329 - mae: 0.6458 - val_loss: 14.9741 - val_mae: 3.0554
Epoch 18/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 47ms/step - loss: 0.7067 - mae: 0.6332 - val_loss: 15.0606 - val_mae: 3.0746
Epoch 19/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 48ms/step - loss: 0.6861 - mae: 0.6238 - val_loss: 15.0830 - val_mae: 3.0668
Epoch 20/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 57s 50ms/step - loss: 0.6635 - mae: 0.6145 - val_loss: 14.9856 - val_mae: 3.0525
Epoch 21/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 51ms/step - loss: 0.6437 - mae: 0.6043 - val_loss: 15.1221 - val_mae: 3.0671
Epoch 22/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 55s 47ms/step - loss: 0.6279 - mae: 0.5961 - val_loss: 14.9206 - val_mae: 3.0538
Epoch 23/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.6256 - mae: 0.5948 - val_loss: 14.7731 - val_mae: 3.0285
Epoch 24/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 49ms/step - loss: 0.5692 - mae: 0.5681 - val_loss: 15.1698 - val_mae: 3.0666
Epoch 25/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 81s 47ms/step - loss: 0.6587 - mae: 0.6068 - val_loss: 14.7331 - val_mae: 3.0186
Epoch 26/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 48ms/step - loss: 0.5472 - mae: 0.5575 - val_loss: 14.9296 - val_mae: 3.0440
Epoch 27/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 55s 48ms/step - loss: 0.5677 - mae: 0.5651 - val_loss: 14.7681 - val_mae: 3.0268
Epoch 28/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 56s 48ms/step - loss: 0.5312 - mae: 0.5481 - val_loss: 14.8629 - val_mae: 3.0393
Epoch 29/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 0.5091 - mae: 0.5384 - val_loss: 14.7687 - val_mae: 3.0232
Epoch 30/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 58s 51ms/step - loss: 0.4967 - mae: 0.5297 - val_loss: 14.5105 - val_mae: 2.9906
```

3. Using a combination of both 1D convents and RNN

```
# Define the Hybrid 1D CNN + LSTM Model
model_cnn_lstm = keras.Sequential([
    layers.Conv1D(filters=32, kernel_size=5, activation="relu", input_shape=(sequence_length, normalized_data.shape[1])),
```

```
    layers.MaxPooling1D(pool_size=2),
    layers.Conv1D(filters=64, kernel_size=5, activation="relu"),
    layers.MaxPooling1D(pool_size=2),
    layers.LSTM(64, return_sequences=True),
    layers.LSTM(32),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model_cnn_lstm.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model_cnn_lstm.summary()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)`
  super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
conv1d (Conv1D)	(None, 116, 32)	2,272
max_pooling1d (MaxPooling1D)	(None, 58, 32)	0
conv1d_1 (Conv1D)	(None, 54, 64)	10,304
max_pooling1d_1 (MaxPooling1D)	(None, 27, 64)	0
lstm_3 (LSTM)	(None, 27, 64)	33,024
lstm_4 (LSTM)	(None, 32)	12,416
dense_4 (Dense)	(None, 1)	33

Total params: 58,049 (226.75 KB)
Trainable params: 58,049 (226.75 KB)
Non-trainable params: 0 (0.00 B)

```
# Define the Hybrid 1D CNN + GRU Model
model_cnn_gru = keras.Sequential([
    layers.Conv1D(filters=32, kernel_size=5, activation="relu", input_shape=(sequence_length, normalized_data.shape[1])),
    layers.MaxPooling1D(pool_size=2),
    layers.Conv1D(filters=64, kernel_size=5, activation="relu"),
    layers.MaxPooling1D(pool_size=2),
    layers.GRU(64, return_sequences=True),
    layers.GRU(32),
    layers.Dense(1)  # Output layer (predicting temperature)
])

# Compile the model
model_cnn_gru.compile(optimizer="adam", loss="mse", metrics=["mae"])

# Display model summary
model_cnn_gru.summary()
```

Model: "sequential_5"

Layer (type)	Output Shape	Param #
conv1d_2 (Conv1D)	(None, 116, 32)	2,272
max_pooling1d_2 (MaxPooling1D)	(None, 58, 32)	0
conv1d_3 (Conv1D)	(None, 54, 64)	10,304
max_pooling1d_3 (MaxPooling1D)	(None, 27, 64)	0
gru_3 (GRU)	(None, 27, 64)	24,960
gru_4 (GRU)	(None, 32)	9,408
dense_5 (Dense)	(None, 1)	33

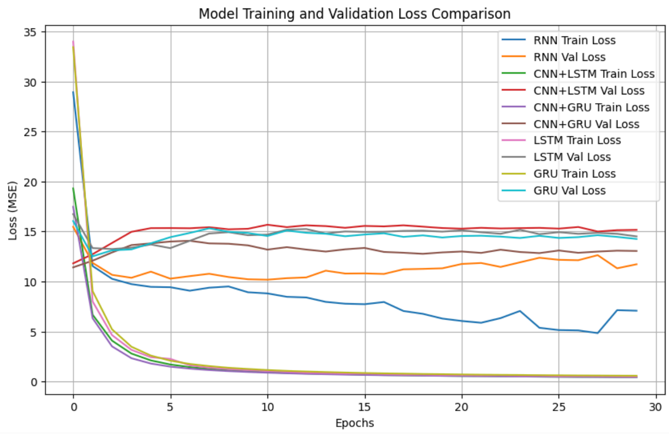
Total params: 46,977 (183.50 KB)
Trainable params: 46,977 (183.50 KB)
Non-trainable params: 0 (0.00 B)

```
# Train CNN + LSTM Model
history_cnn_lstm = model_cnn_lstm.fit(
    train_dataset,
    epochs=30,
    validation_data=val_dataset
)

# Train CNN + GRU Model
history_cnn_gru = model_cnn_gru.fit(
    train_dataset,
    epochs=30,
    validation_data=val_dataset
)
```

```
Epoch 1/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 42ms/step - loss: 36.6756 - mae: 4.3489 - val_loss: 11.8131 - val_mae: 2.6410
Epoch 2/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 47s 41ms/step - loss: 7.5350 - mae: 2.1200 - val_loss: 12.7298 - val_mae: 2.7929
Epoch 3/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 42ms/step - loss: 4.5818 - mae: 1.6491 - val_loss: 13.8540 - val_mae: 2.9466
Epoch 4/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 49s 42ms/step - loss: 3.0175 - mae: 1.3387 - val_loss: 14.9679 - val_mae: 3.0667
Epoch 5/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 45ms/step - loss: 2.2351 - mae: 1.1528 - val_loss: 15.3354 - val_mae: 3.1056
Epoch 6/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 1.7839 - mae: 1.0296 - val_loss: 15.3424 - val_mae: 3.1053
Epoch 7/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 54s 47ms/step - loss: 1.4920 - mae: 0.9422 - val_loss: 15.3232 - val_mae: 3.1107
Epoch 8/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 78s 44ms/step - loss: 1.2865 - mae: 0.8746 - val_loss: 15.4284 - val_mae: 3.1023
Epoch 9/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 52s 45ms/step - loss: 1.1330 - mae: 0.8205 - val_loss: 15.2183 - val_mae: 3.0875
Epoch 10/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 1.0422 - mae: 0.7864 - val_loss: 15.2703 - val_mae: 3.0892
Epoch 11/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 53s 46ms/step - loss: 0.9399 - mae: 0.7464 - val_loss: 15.6736 - val_mae: 3.1397
Epoch 12/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 0.8723 - mae: 0.7183 - val_loss: 15.4352 - val_mae: 3.1170
Epoch 13/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 0.8117 - mae: 0.6927 - val_loss: 15.6170 - val_mae: 3.1237
Epoch 14/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 45ms/step - loss: 0.7750 - mae: 0.6760 - val_loss: 15.5389 - val_mae: 3.1153
Epoch 15/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 45ms/step - loss: 0.7434 - mae: 0.6633 - val_loss: 15.3684 - val_mae: 3.1001
Epoch 16/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 0.6735 - mae: 0.6307 - val_loss: 15.5563 - val_mae: 3.1100
Epoch 17/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 83s 45ms/step - loss: 0.6534 - mae: 0.6218 - val_loss: 15.5088 - val_mae: 3.1002
Epoch 18/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 50s 44ms/step - loss: 0.6275 - mae: 0.6079 - val_loss: 15.6175 - val_mae: 3.1157
Epoch 19/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 41ms/step - loss: 0.5962 - mae: 0.5928 - val_loss: 15.4828 - val_mae: 3.0937
Epoch 20/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 47s 41ms/step - loss: 0.5741 - mae: 0.5824 - val_loss: 15.3457 - val_mae: 3.0781
Epoch 21/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 41ms/step - loss: 0.5545 - mae: 0.5718 - val_loss: 15.2807 - val_mae: 3.0864
Epoch 22/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 51s 44ms/step - loss: 0.5419 - mae: 0.5653 - val_loss: 15.3672 - val_mae: 3.0858
Epoch 23/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 78s 41ms/step - loss: 0.5231 - mae: 0.5557 - val_loss: 15.3013 - val_mae: 3.0772
Epoch 24/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 41ms/step - loss: 0.5073 - mae: 0.5474 - val_loss: 15.3361 - val_mae: 3.0687
Epoch 25/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 85s 44ms/step - loss: 0.4930 - mae: 0.5386 - val_loss: 15.3625 - val_mae: 3.0792
Epoch 26/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 41ms/step - loss: 0.4753 - mae: 0.5298 - val_loss: 15.2864 - val_mae: 3.0663
```

```
Epoch 27/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 82s 41ms/step - loss: 0.4594 - mae: 0.5214 - val_loss: 15.4494 - val_mae: 3.0757
Epoch 28/30
1145/1145 ━━━━━━━━━━━━━━━━━━━━ 48s 42ms/step - loss: 0.4548 - mae: 0.5174 - val_loss: 14.9969 - val_mae: 3.0351
Epoch 29/30
```

```python
# Function to plot training curves
def plot_training_curves(history, model_name):
    # Training and validation loss
    plt.plot(history.history['loss'], label=f'{model_name} Train Loss')
    plt.plot(history.history['val_loss'], label=f'{model_name} Val Loss')

# Plot training curves for each model
plt.figure(figsize=(10, 6))

#plot simple Stacked RNN model
plot_training_curves(history, "RNN")

# CNN + LSTM
plot_training_curves(history_cnn_lstm, "CNN+LSTM")

# CNN + GRU
plot_training_curves(history_cnn_gru, "CNN+GRU")

# LSTM
plot_training_curves(history_lstm, "LSTM")

# GRU
plot_training_curves(history_gru, "GRU")

# Add labels and legend
plt.title("Model Training and Validation Loss Comparison")
plt.xlabel("Epochs")
plt.ylabel("Loss (MSE)")
plt.legend()
plt.grid(True)
plt.show()
```



Prediction using CNN+GRU

```python
# Make predictions using the CNN+GRU model
predictions = model_cnn_gru.predict(test_dataset)

# Print the shape of the predictions to verify
print("Predictions Shape:", predictions.shape)
```

```
244/244 ━━━━━━━━━━━━━━━━━━━━ 8s 30ms/step
Predictions Shape: (62226, 1)
```

```python
# Get the actual temperature values (from the test dataset)
actual_values = []
for _, labels in test_dataset:
    actual_values.append(labels.numpy())  # Extracting the actual temperature values
actual_values = np.concatenate(actual_values, axis=0)

# Plotting the actual vs predicted values
plt.figure(figsize=(10, 6))
plt.plot(actual_values, label="Actual Temperature", color="blue")
plt.plot(predictions, label="Predicted Temperature", color="red", linestyle="--")
plt.title("Actual vs Predicted Temperature (CNN+GRU)")
plt.xlabel("Time Steps")
plt.ylabel("Temperature")
plt.legend()
plt.show()
```