```
!pip install tensorflow==2.12
```

```
Requirement already satisfied: tensorflow==2.12 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: flatbuffers>=2.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: gast<=0.4.0,>=0.2.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: jax>=0.3.15 in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: keras<2.13,>=2.12.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: numpy<1.24,>=1.22 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (fro
Requirement already satisfied: protobuf!=4.21.0,!=4.21.1,!=4.21.2,!=4.21.3,!=4.21.4,!=4.
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (fr
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (f
Requirement already satisfied: tensorboard<2.13,>=2.12 in /usr/local/lib/python3.10/dist
Requirement already satisfied: tensorflow-estimator<2.13,>=2.12.0 in /usr/local/lib/pyth
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/dis
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/py
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: ml-dtypes>=0.2.0 in /usr/local/lib/python3.10/dist-packag
Requirement already satisfied: scipy>=1.9 in /usr/local/lib/python3.10/dist-packages (fr
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /usr/local/lib/python3.
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-pac
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/p
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.10/dist-package
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.10/dist-
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.10/dist-p
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.10/dist-packages
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.10/dis
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dis
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-pack
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.10/dist-packa
Requirement already satisfied: pyasn1<0.7.0,>=0.4.6 in /usr/local/lib/python3.10/dist-pa
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.10/dist-package
```

Dataset

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

```
--2024-07-19 22:58:22--  https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.
Resolving s3.amazonaws.com (s3.amazonaws.com)... 52.217.203.0, 52.217.192.152, 16.182.67
Connecting to s3.amazonaws.com (s3.amazonaws.com)|52.217.203.0|: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  53.7MB/s    in 0.2s

2024-07-19 22:58:22 (53.7 MB/s) - ‘jena_climate_2009_2016.csv.zip’ saved [13565642/13565

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

Jena weather dataset

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

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

line1 = data.split("\n")
header1 = line1[0].split(",")
line1 = line1[1:]
print(header1)
print(len(line1))

num_var = len(header1)
print("Number of variables:", num_var)
num_rows = len(line1)
print("Number of rows:", num_rows)
```

```
['"Date Time"', '"p (mbar)"', '"T (degC)"', '"Tpot (K)"', '"Tdew (degC)"', '"rh (%)"', '
420451
Number of variables: 15
Number of rows: 420451
```

Dataset contains 420451 rows and 15 features

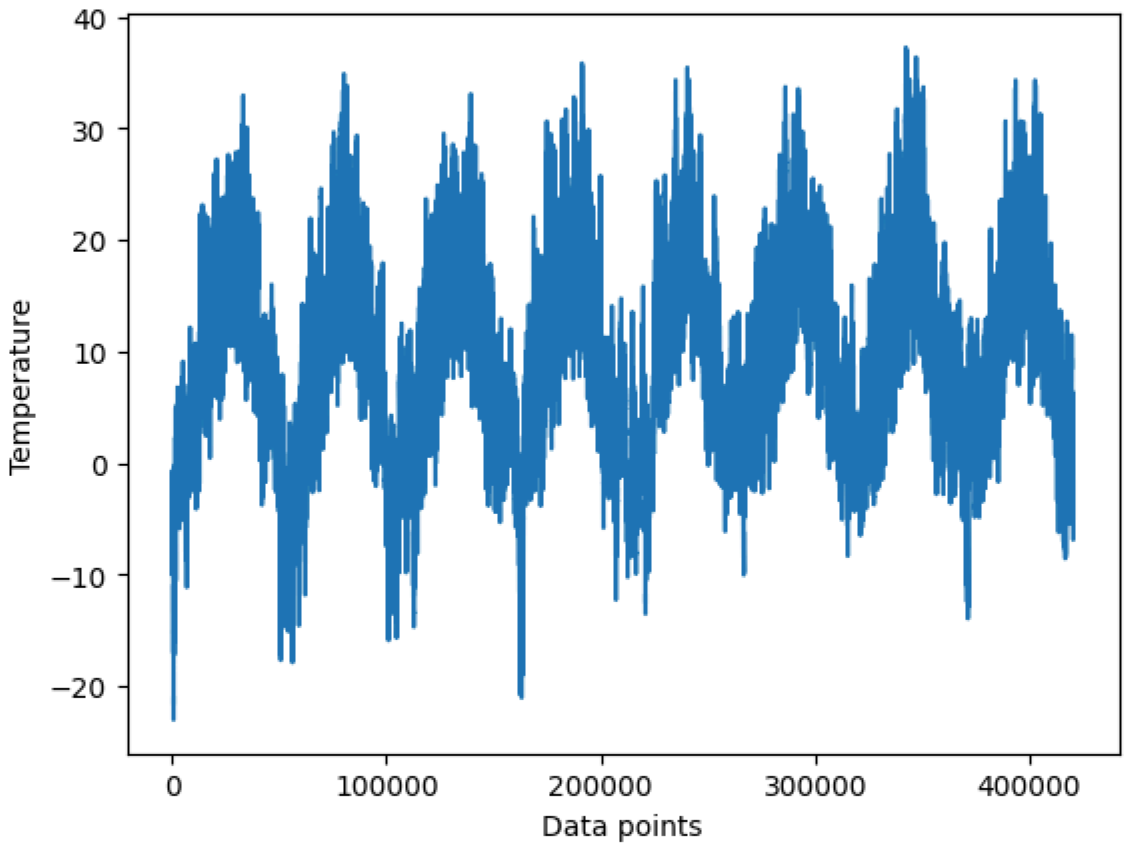
Following the data analysis, specific values are saved in the raw_data and temperature arrays for subsequent processing or analysis. Comma-separated values are converted into floating-point numbers.

```
import numpy as np
temp1 = np.zeros((len(line1),))
raw_d = np.zeros((len(line1), len(header1) - 1))
for i, line in enumerate(line1):
    values = [float(x) for x in line.split(",")[1:]]
    temp1[i] = values[1]
    raw_d[i, :] = values[:]
```

The timeseries plot of temperature

```
from matplotlib import pyplot as plt
plt.plot(range(len(temp1)), temp1)
plt.xlabel('Data points')
plt.ylabel('Temperature')
```

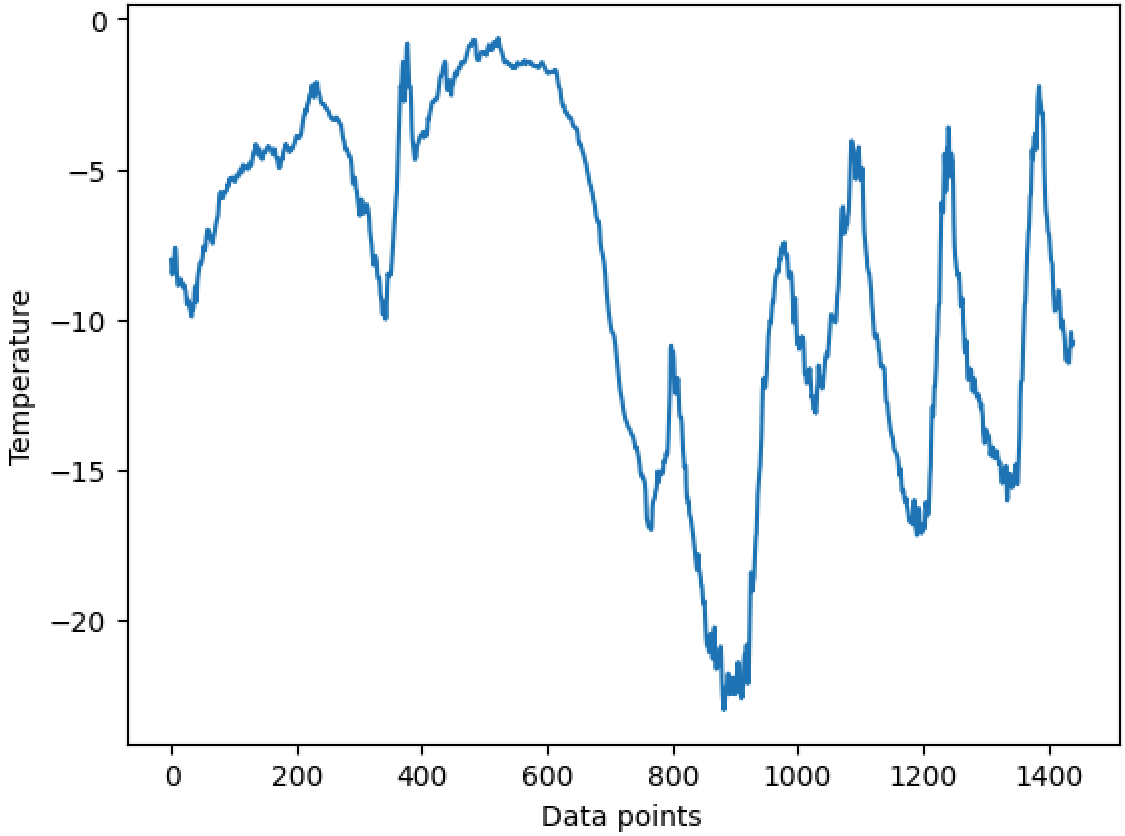
```
Text(0, 0.5, 'Temperature')
```



The temperature time series for the first ten days is plotted. Since each day consists of 144 data points, ten days will produce a total of 1440 data points.

```
plt.plot(range(1440), temp1[:1440])
plt.xlabel('Data points')
plt.ylabel('Temperature')
```

```
Text(0, 0.5, 'Temperature')
```



Calculating the number of samples needed for each data split, with 25% allocated for validation and 50% for training.

```
num_of_train = int(0.5 * len(raw_d))
num_of_val= int(0.25 * len(raw_d))
num_of_test= len(raw_d) - num_of_train - num_of_val
print("Number of train samples:", num_of_train)
print("Number of validation samples:", num_of_val)
print("Number of test samples:", num_of_test)
```

```
Number of train samples: 210225
Number of validation samples: 105112
Number of test samples: 105114
```

Getting the information ready

Since the data is already in numerical form, vectorization is unnecessary. However, it is important to standardize all variables due to differences in their scales (e.g., temperature ranges from -20 to +30, while pressure is measured in millibars).

```
mean1 = raw_d[:num_of_train].mean(axis=0)
raw_d -= mean1
std = raw_d[:num_of_train].std(axis=0)
raw_d /= std
```

```
import numpy as np
from tensorflow import keras
int_sequence1 = np.arange(10)
dummy_d = keras.utils.timeseries_dataset_from_array(
    data=int_sequence1[:-3],
    targets=int_sequence1[3:],
    sequence_length=3,
    batch_size=2,
)

for inputs, targets in dummy_d:
    for i in range(inputs.shape[0]):
        print([int(x) for x in inputs[i]], int(targets[i]))
```

```
[0, 1, 2] 3
[1, 2, 3] 4
[2, 3, 4] 5
[3, 4, 5] 6
[4, 5, 6] 7
```

It is essential to create separate training, validation, and testing datasets because of the significant duplication within the dataset. Allocating RAM for every sample would be inefficient, so samples will be generated in real-time instead.

```
sample_rate = 6
sequencelength = 120
delay = sample_rate * (sequencelength + 24 - 1)
batch_size = 256

training_data = keras.utils.timeseries_dataset_from_array(
    raw_d[:-delay],
    targets=temp1[delay:],
    sampling_rate=sample_rate,
    sequence_length=sequencelength,
    shuffle=True,
    batch_size=batch_size,
    start_index=0,
    end_index=num_of_train)

validation_data = keras.utils.timeseries_dataset_from_array(
    raw_d[:-delay],
    targets=temp1[delay:],
    sampling_rate=sample_rate,
    sequence_length=sequencelength,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_of_train,
    end_index=num_of_train + num_of_val)

testing_data = keras.utils.timeseries_dataset_from_array(
    raw_d[:-delay],
    targets=temp1[delay:],
    sampling_rate=sample_rate,
    sequence_length=sequencelength,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_of_train + num_of_val)
```

Result of the databases

```
for samples, targets in training_data:
    print("samples shape:", samples.shape)
    print("targets shape:", targets.shape)
    break
```

```
samples shape: (256, 120, 14)
targets shape: (256,)
```

**A practical baseline not driven by machine learning:

Setting the baseline MAE involves using the final value in the input sequence as the starting point. The function "evaluate_naive_method" is defined for this purpose, providing a reference for evaluating the performance of a simple forecasting approach.**

```
def evaluate_naive_method(dataset):
    total_absolute_error = 0.
    samples_saw = 0
    for samples, targets in dataset:
        preds = samples[:, -1, 1] * std[1] + mean1[1]
        total_absolute_error += np.sum(np.abs(preds - targets))
        samples_saw += samples.shape[0]
    return total_absolute_error / samples_saw

print(f"Validation MAE: {evaluate_naive_method(validation_data):.2f}")
print(f"Test MAE: {evaluate_naive_method(testing_data):.2f}")
```

```
Validation MAE: 2.44
Test MAE: 2.62
```

**A straightforward approach is to predict that the temperature will stay the same over the next 24 hours. With this basic baseline, the test mean is 2.62 degrees Celsius, and the validation mean absolute error (MAE) is 2.44 degrees. In other words, if future temperatures were to remain constant, the average deviation from the actual temperature would be approximately 2.5 degrees.

Introduction to Machine Learning: Dense Layer

Training and evaluating a densely connected model.**

```
from tensorflow import keras
from tensorflow.keras import layers

inputs = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
G1 = layers.Flatten()(inputs)
G1 = layers.Dense(16, activation="relu")(G1)
outputs = layers.Dense(1)(G1)
model = keras.Model(inputs, outputs)


callbacks = [
    keras.callbacks.ModelCheckpoint("jena_dense.keras",
                                    save_best_only=True)]

model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])


history = model.fit(training_data, epochs=5,
                    validation_data = validation_data, callbacks=callbacks)
```

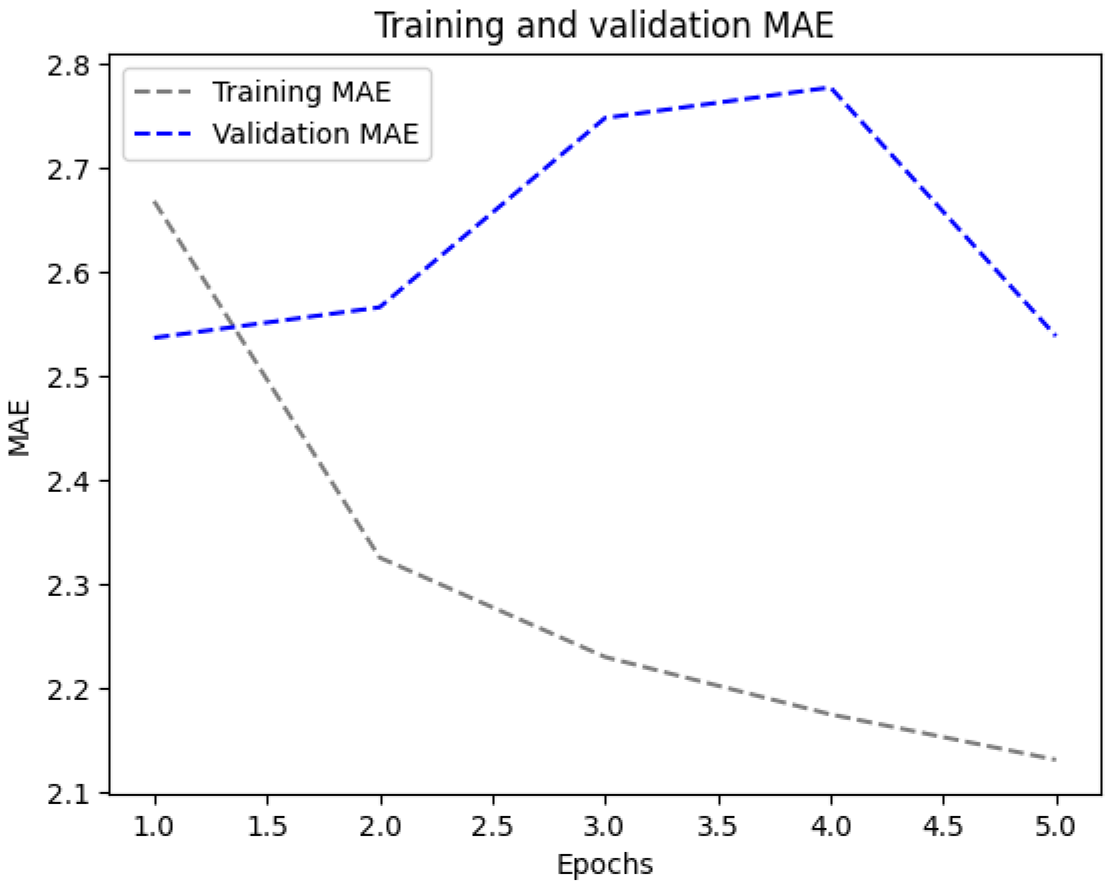
```
===] - 62s 75ms/step - loss: 11.8984 - mae: 2.6682 - val_loss: 10.4127 - val_mae: 2.5368
```

```
===] - 56s 68ms/step - loss: 8.7366 - mae: 2.3255 - val_loss: 10.5348 - val_mae: 2.5662

===] - 55s 66ms/step - loss: 8.0174 - mae: 2.2298 - val_loss: 12.1098 - val_mae: 2.7483

===] - 56s 67ms/step - loss: 7.6246 - mae: 2.1747 - val_loss: 12.4215 - val_mae: 2.7777

===] - 58s 71ms/step - loss: 7.3286 - mae: 2.1310 - val_loss: 10.3855 - val_mae: 2.5385
```

```
model = keras.models.load_model("jena_dense.keras")
print(f"Test MAE: {model.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 18s 44ms/step - loss: 11.1121 - mae: 2.6466
Test MAE: 2.65
```

```
import matplotlib.pyplot as plt
loss1 = history.history["mae"]
validation_loss = history.history["val_mae"]

epochs = range(1, len(loss1) + 1)
plt.figure()
plt.plot(epochs, loss1, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss, color="blue",linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



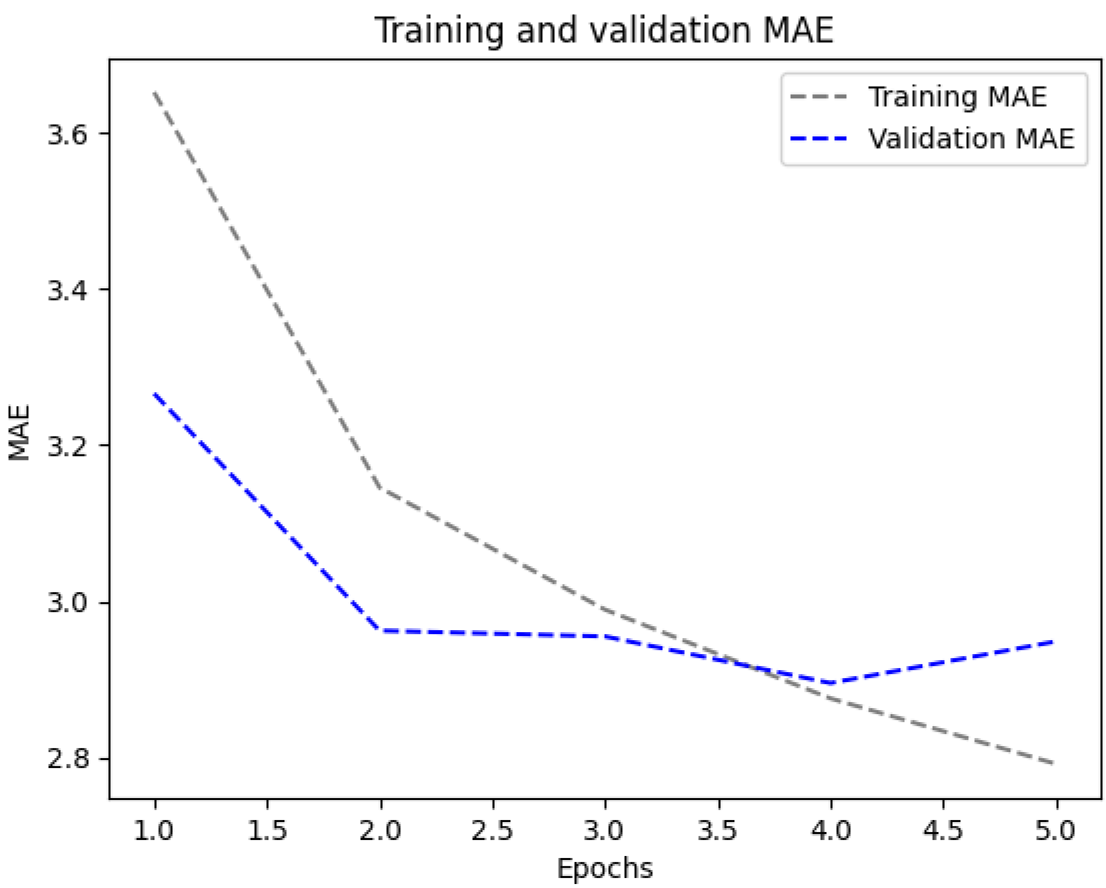
1D convolutional model.

```
inputs = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
x = layers.Conv1D(8, 24, activation="relu")(inputs)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 12, activation="relu")(x)
x = layers.MaxPooling1D(2)(x)
x = layers.Conv1D(8, 6, activation="relu")(x)
x = layers.GlobalAveragePooling1D()(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)
```

```
callbacks = [
    keras.callbacks.ModelCheckpoint("jena_conv.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history1D = model.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)

model_to_dot = keras.models.load_model("jena_conv.keras")
print(f"Test MAE: {model.evaluate(testing_data)[1]:.2f}")
```

```
Epoch 1/5
819/819 [==============================] - 114s 137ms/step - loss: 21.4170 - mae: 3.652
Epoch 2/5
819/819 [==============================] - 92s 112ms/step - loss: 15.6015 - mae: 3.1457
Epoch 3/5
819/819 [==============================] - 90s 110ms/step - loss: 14.1345 - mae: 2.9893
Epoch 4/5
819/819 [==============================] - 98s 119ms/step - loss: 13.1210 - mae: 2.8755
Epoch 5/5
819/819 [==============================] - 119s 145ms/step - loss: 12.4102 - mae: 2.791
405/405 [==============================] - 22s 53ms/step - loss: 15.5466 - mae: 3.1669
Test MAE: 3.17
```

```
import matplotlib.pyplot as plt
loss1D = history1D.history["mae"]
validation_loss1D = history1D.history["val_mae"]

epochs = range(1, len(loss1D) + 1)
plt.figure()
plt.plot(epochs, loss1D, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss1D, color="blue",linestyle="dashed", label="Validation MAE"
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



Convolutional data seems to perform worse than dense models or common-sense approaches. This may be due to:

Weather data does not satisfy the translation invariance assumption. The order in which information is presented is crucial. For predicting the temperature for the next day, recent historical data is significantly more relevant than data from many days prior. Unfortunately, a 1D convolutional neural network cannot adequately represent this important temporal order.

A Basic RNN:

1. An RNN layer capable of handling sequences of any length.

```
the_features = 14
input_RNN = keras.Input(shape=(None, the_features))
output_RNN = layers.SimpleRNN(16)(input_RNN)

models_RNN = keras.Model(input_RNN, output_RNN)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_SimRNN.keras",
                                    save_best_only=True)
]
models_RNN.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_RNN = models_RNN.fit(training_data,
```

```
history_RNN = models_RNN.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)

models_RNN = keras.models.load_model("jena_SimRNN.keras")
print(f"Test MAE: {models_RNN.evaluate(testing_data)[1]:.2f}")
```

```
Epoch 1/5
819/819 [==============================] - 80s 95ms/step - loss: 138.6137 - mae: 9.6887
Epoch 2/5
819/819 [==============================] - 80s 97ms/step - loss: 136.4938 - mae: 9.5668
Epoch 3/5
819/819 [==============================] - 81s 98ms/step - loss: 136.3223 - mae: 9.5527
Epoch 4/5
819/819 [==============================] - 82s 100ms/step - loss: 136.2020 - mae: 9.540
Epoch 5/5
819/819 [==============================] - 83s 101ms/step - loss: 136.1723 - mae: 9.539
405/405 [==============================] - 21s 51ms/step - loss: 151.3202 - mae: 9.9222
Test MAE: 9.92
```

2.Simple RNN - Stacking RNN layers

```
the_features2 = 14
steps = 120
inpu2 = keras.Input(shape=(steps, the_features2))
a = layers.SimpleRNN(16, return_sequences=True)(inpu2)
a = layers.SimpleRNN(16, return_sequences=True)(a)
outpu2 = layers.SimpleRNN(16)(a)
models2 = keras.Model(inpu2, outpu2)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_SRNN2.keras",
                                    save_best_only=True)
]
models2.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history2 = models2.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)

models2 = keras.models.load_model("jena_SRNN2.keras")
print(f"Test MAE: {models2.evaluate(testing_data)[1]:.2f}")
```

```
Epoch 1/5
819/819 [==============================] - 158s 188ms/step - loss: 136.7013 - mae: 9.56
Epoch 2/5
819/819 [==============================] - 154s 188ms/step - loss: 136.0209 - mae: 9.52
Epoch 3/5
819/819 [==============================] - 145s 177ms/step - loss: 135.9623 - mae: 9.51
```

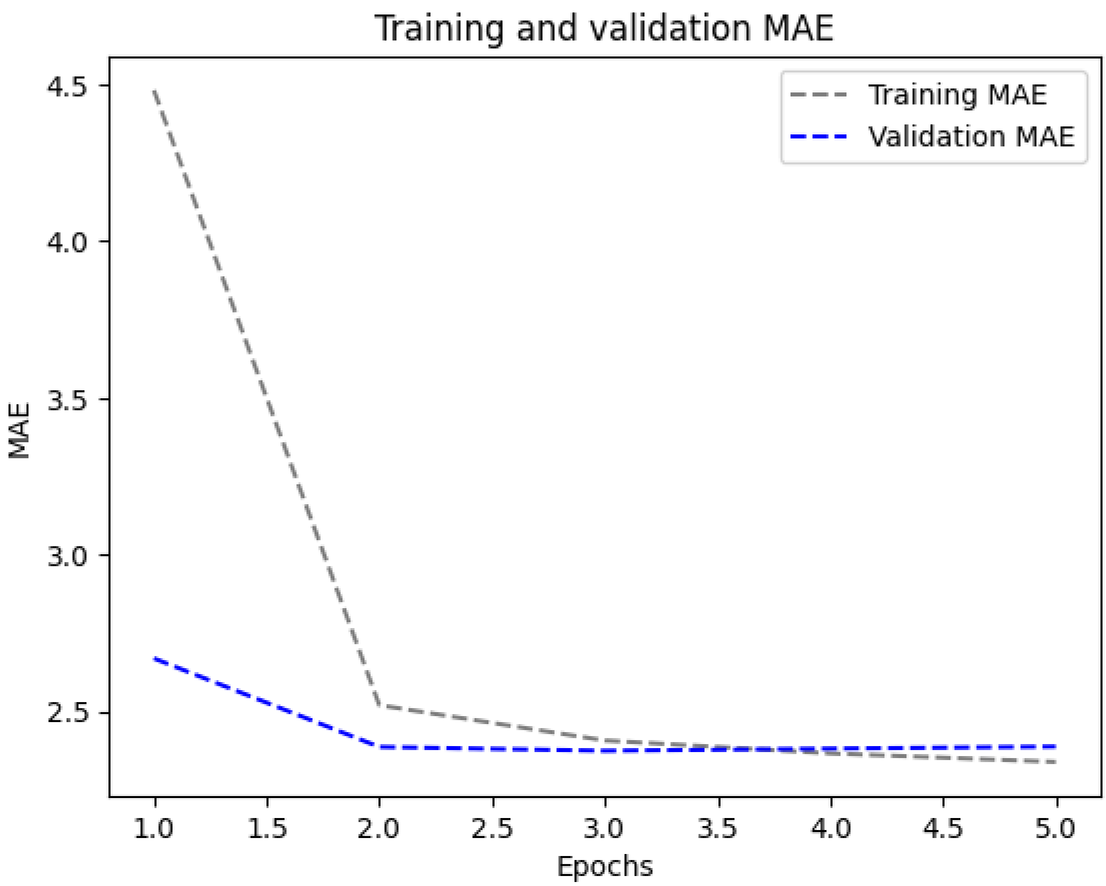
```
Epoch 4/5
819/819 [==============================] - 143s 174ms/step - loss: 135.9179 - mae: 9.507
Epoch 5/5
819/819 [==============================] - 140s 171ms/step - loss: 135.8698 - mae: 9.506
405/405 [==============================] - 33s 79ms/step - loss: 151.1238 - mae: 9.9046
Test MAE: 9.90
```

Simple GRU (Gated Recurrent Unit)

```
inputs_GRU = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
b = layers.GRU(16)(inputs_GRU)
outputs_GRU = layers.Dense(1)(b)
models_GRU = keras.Model(inputs_GRU, outputs_GRU)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_gru.keras",
                                    save_best_only=True)
]
models_GRU.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_GRU = models_GRU.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)

models_GRU = keras.models.load_model("jena_gru.keras")
print(f"Test MAE: {models_GRU.evaluate(testing_data)[1]:.2f}")
```

```
Epoch 1/5
819/819 [==============================] - 140s 167ms/step - loss: 38.3551 - mae: 4.4818
Epoch 2/5
819/819 [==============================] - 117s 143ms/step - loss: 10.4565 - mae: 2.5196
Epoch 3/5
819/819 [==============================] - 137s 167ms/step - loss: 9.4895 - mae: 2.4069
Epoch 4/5
819/819 [==============================] - 137s 166ms/step - loss: 9.1913 - mae: 2.3659
Epoch 5/5
819/819 [==============================] - 138s 168ms/step - loss: 8.9676 - mae: 2.3386
405/405 [==============================] - 28s 67ms/step - loss: 10.2381 - mae: 2.5054
Test MAE: 2.51
```

```
import matplotlib.pyplot as plt
loss_GRU = history_GRU.history["mae"]
validation_loss_GRU = history_GRU.history["val_mae"]

epochs = range(1, len(loss_GRU) + 1)
plt.figure()
plt.plot(epochs, loss_GRU, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_GRU, color="blue",linestyle="dashed", label="Validation MA
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



LSTM(Long Short-Term Memory)

1.LSTM-Simple

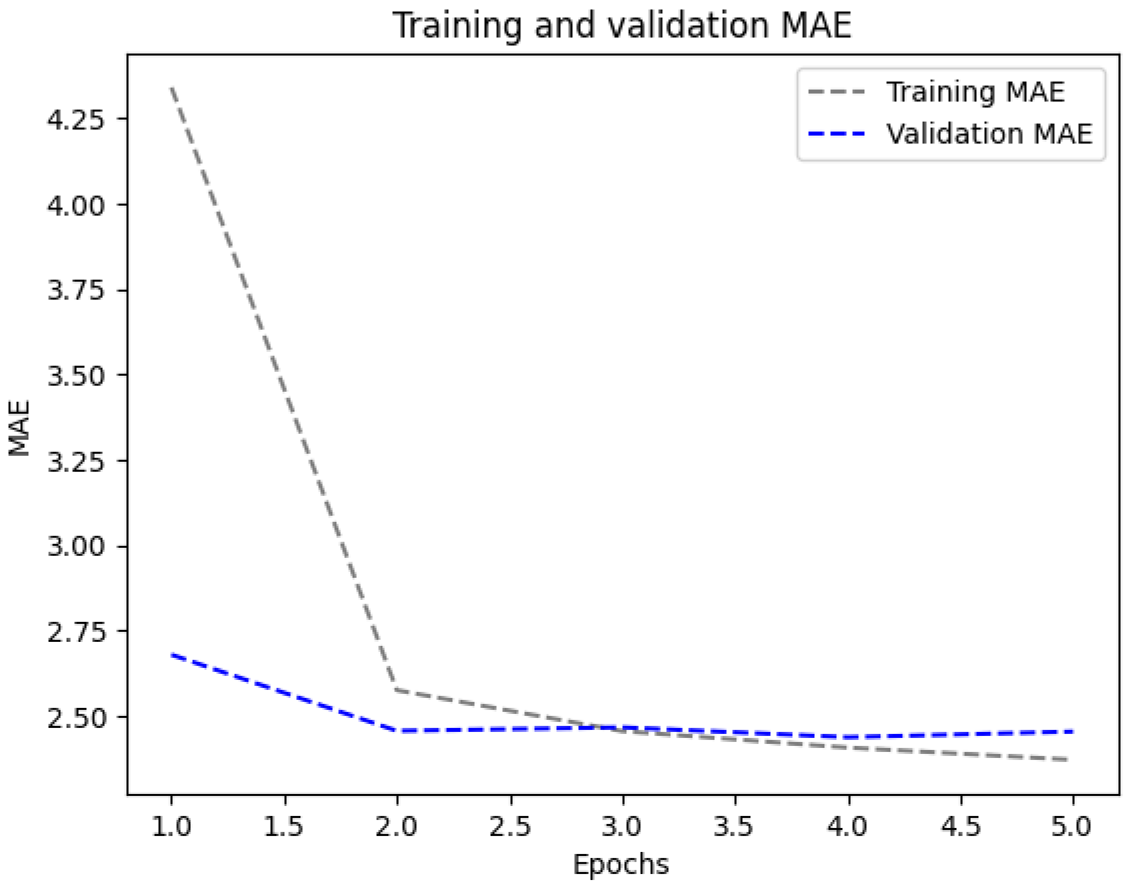
```
inputs_LSTMS = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
c = layers.LSTM(16)(inputs_LSTMS)
output_LSTMS = layers.Dense(1)(c)
model_LSTMS = keras.Model(inputs_LSTMS, output_LSTMS)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm.keras",
                                    save_best_only=True)
]
model_LSTMS.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_LSTMS = model_LSTMS.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
Epoch 1/5
819/819 [==============================] - 125s 148ms/step - loss: 35.7270 - mae: 4.340
Epoch 2/5
819/819 [==============================] - 118s 144ms/step - loss: 10.9732 - mae: 2.574
Epoch 3/5
819/819 [==============================] - 134s 163ms/step - loss: 9.8415 - mae: 2.4549
Epoch 4/5
819/819 [==============================] - 123s 150ms/step - loss: 9.4615 - mae: 2.4067
Epoch 5/5
819/819 [==============================] - 119s 145ms/step - loss: 9.1633 - mae: 2.3711
```

```
model_LSTMS = keras.models.load_model("jena_lstm.keras")
print(f"Test MAE: {model_LSTMS.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 31s 75ms/step - loss: 10.9850 - mae: 2.5772
Test MAE: 2.58
```

```
import matplotlib.pyplot as plt
loss_LSTMS = history_LSTMS.history["mae"]
validation_loss_LSTMS = history_LSTMS.history["val_mae"]

epochs = range(1, len(loss_LSTMS) + 1)
plt.figure()
plt.plot(epochs, loss_LSTMS, color="grey", linestyle="dashed", label="Training MA
plt.plot(epochs,  validation_loss_LSTMS, color="blue",linestyle="dashed", label="
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



2.LSTM - dropout Regularization

```
input_LSTMR = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
d = layers.LSTM(16, recurrent_dropout=0.25)(input_LSTMR )
d = layers.Dropout(0.5)(d)
output_LSTMR = layers.Dense(1)(d)
model_LSTMR = keras.Model(input_LSTMR , output_LSTMR )

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_lstm_dropout.keras",
                                    save_best_only=True)
]
model_LSTMR.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_LSTMR = model_LSTMR.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

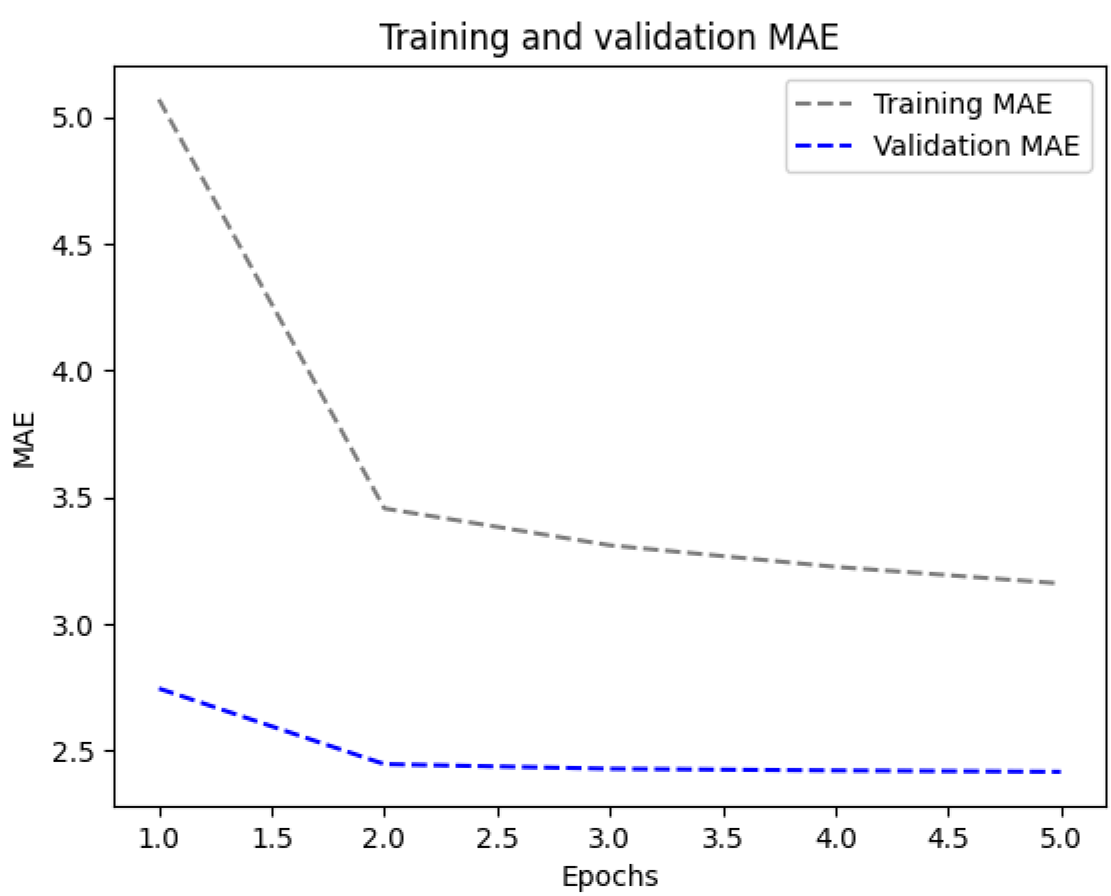
```
Epoch 1/5
819/819 [==============================] - 191s 229ms/step - loss: 46.5135 - mae: 5.0684
Epoch 2/5
819/819 [==============================] - 188s 230ms/step - loss: 20.0744 - mae: 3.4541
Epoch 3/5
819/819 [==============================] - 194s 237ms/step - loss: 18.4397 - mae: 3.3087
Epoch 4/5
```

```
819/819 [==============================] - 187s 228ms/step - loss: 17.5101 - mae: 3.2237
Epoch 5/5
819/819 [==============================] - 186s 227ms/step - loss: 16.8144 - mae: 3.1579
```

```
model_LSTMR = keras.models.load_model("jena_lstm_dropout.keras")
print(f"Test MAE: {model_LSTMR.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 31s 76ms/step - loss: 11.2013 - mae: 2.6277
Test MAE: 2.63
```

```
import matplotlib.pyplot as plt
loss_LSTMR = history_LSTMR .history["mae"]
validation_loss_LSTMR = history_LSTMR .history["val_mae"]

epochs = range(1, len(loss_LSTMR) + 1)
plt.figure()
plt.plot(epochs, loss_LSTMR, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_LSTMR, color="blue",linestyle="dashed", label="Validation
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



3.LSTM - Stacked setup with 16 units

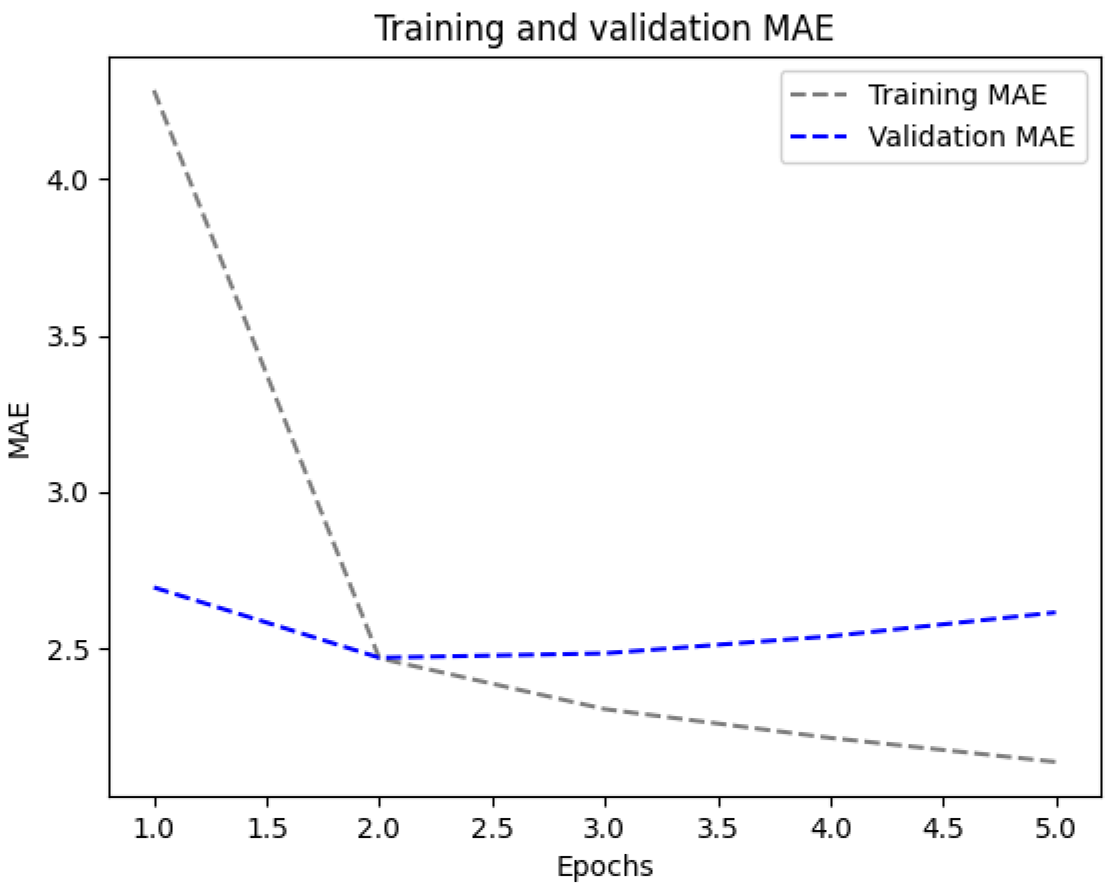
```
input_16 = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
e = layers.LSTM(16, return_sequences=True)(input_16)
e = layers.LSTM(16)(e)
output_16 = layers.Dense(1)(e)
model_16 = keras.Model(input_16, output_16)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked1.keras",
                                    save_best_only=True)
]
model_16.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_16 = model_16.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
=] - 204s 242ms/step - loss: 34.6623 - mae: 4.2848 - val_loss: 12.3141 - val_mae: 2.6937

=] - 195s 238ms/step - loss: 10.0681 - mae: 2.4668 - val_loss: 9.9165 - val_mae: 2.4686

=] - 196s 239ms/step - loss: 8.7171 - mae: 2.3039 - val_loss: 9.9251 - val_mae: 2.4825

=] - 194s 236ms/step - loss: 8.0360 - mae: 2.2119 - val_loss: 10.4227 - val_mae: 2.5373

=] - 196s 239ms/step - loss: 7.4948 - mae: 2.1350 - val_loss: 11.0109 - val_mae: 2.6135
```

```
model_16 = keras.models.load_model("jena_LSTM_stacked1.keras")
print(f"Test MAE: {model_16.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 48s 113ms/step - loss: 11.4072 - mae: 2.6215
Test MAE: 2.62
```

```
import matplotlib.pyplot as plt
loss_16 = history_16.history["mae"]
validation_loss_16 = history_16.history["val_mae"]

epochs = range(1, len(loss_16) + 1)
plt.figure()
plt.plot(epochs, loss_16, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_16, color="blue",linestyle="dashed", label="Validation MAE
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



4.LSTM - Stacked setup with 32 units

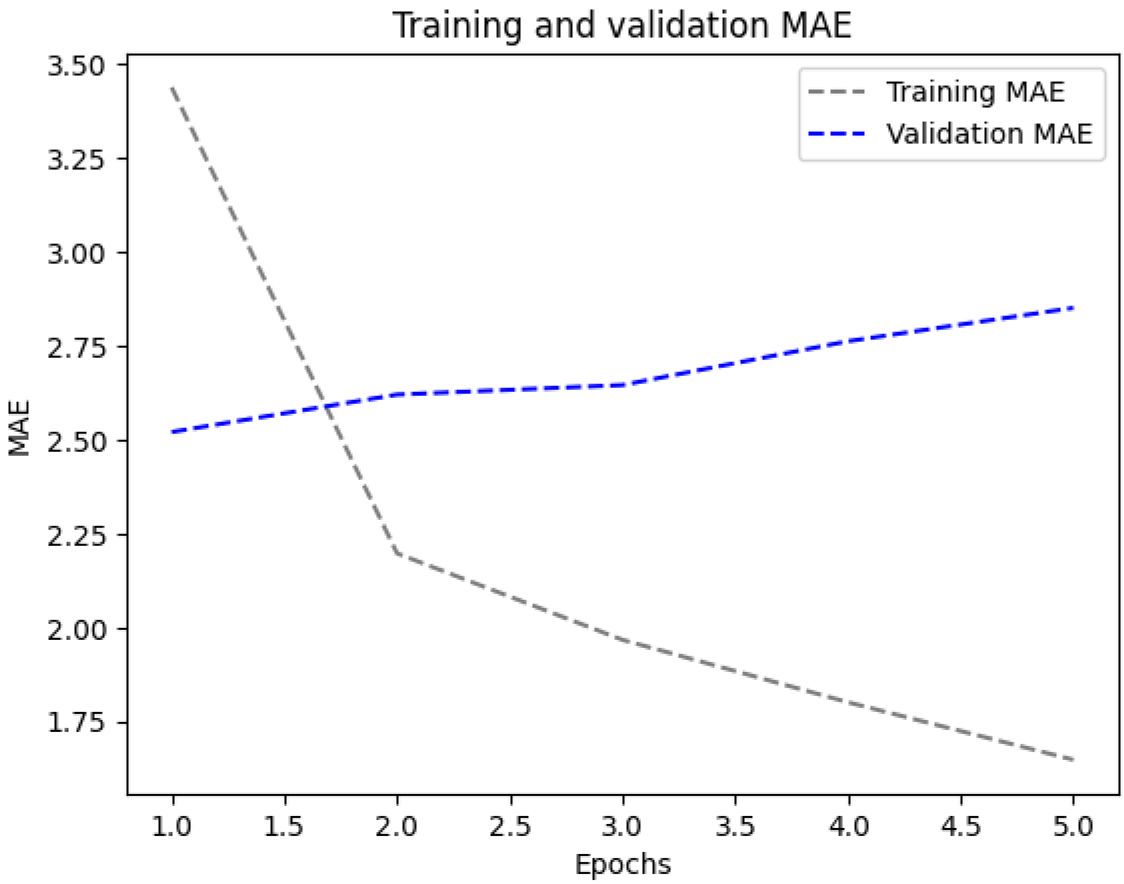
```
input_32 = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
f = layers.LSTM(32, return_sequences=True)(input_32)
f = layers.LSTM(32)(f)
output_32 = layers.Dense(1)(f)
model_32 = keras.Model(input_32, output_32)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked2.keras",
                                    save_best_only=True)
]
model_32.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_32 = model_32.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
=] - 284s 341ms/step - loss: 23.4409 - mae: 3.4376 - val_loss: 10.5010 - val_mae: 2.5203

=] - 276s 337ms/step - loss: 7.9627 - mae: 2.1972 - val_loss: 11.0106 - val_mae: 2.6200

=] - 319s 390ms/step - loss: 6.4367 - mae: 1.9671 - val_loss: 11.2705 - val_mae: 2.6453

=] - 310s 378ms/step - loss: 5.4211 - mae: 1.8009 - val_loss: 12.1361 - val_mae: 2.7620

=] - 306s 373ms/step - loss: 4.5406 - mae: 1.6479 - val_loss: 12.8525 - val_mae: 2.8507
```

```
model_32 = keras.models.load_model("jena_LSTM_stacked2.keras")
print(f"Test MAE: {model_32.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 57s 134ms/step - loss: 11.5211 - mae: 2.6479
Test MAE: 2.65
```

```
import matplotlib.pyplot as plt
loss_32 = history_32.history["mae"]
validation_loss_32 = history_32.history["val_mae"]

epochs = range(1, len(loss_32) + 1)
plt.figure()
plt.plot(epochs, loss_32, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_32, color="blue",linestyle="dashed", label="Validation MAE
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



5.LSTM - Stacked setup with 8 units

```
input_8u = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
h = layers.LSTM(8, return_sequences=True)(input_8u)
h = layers.LSTM(8)(h)
output_8u = layers.Dense(1)(h)
model_8u = keras.Model(input_8u, output_8u)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked3.keras",
                                    save_best_only=True)
]
model_8u.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history_8u = model_8u.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

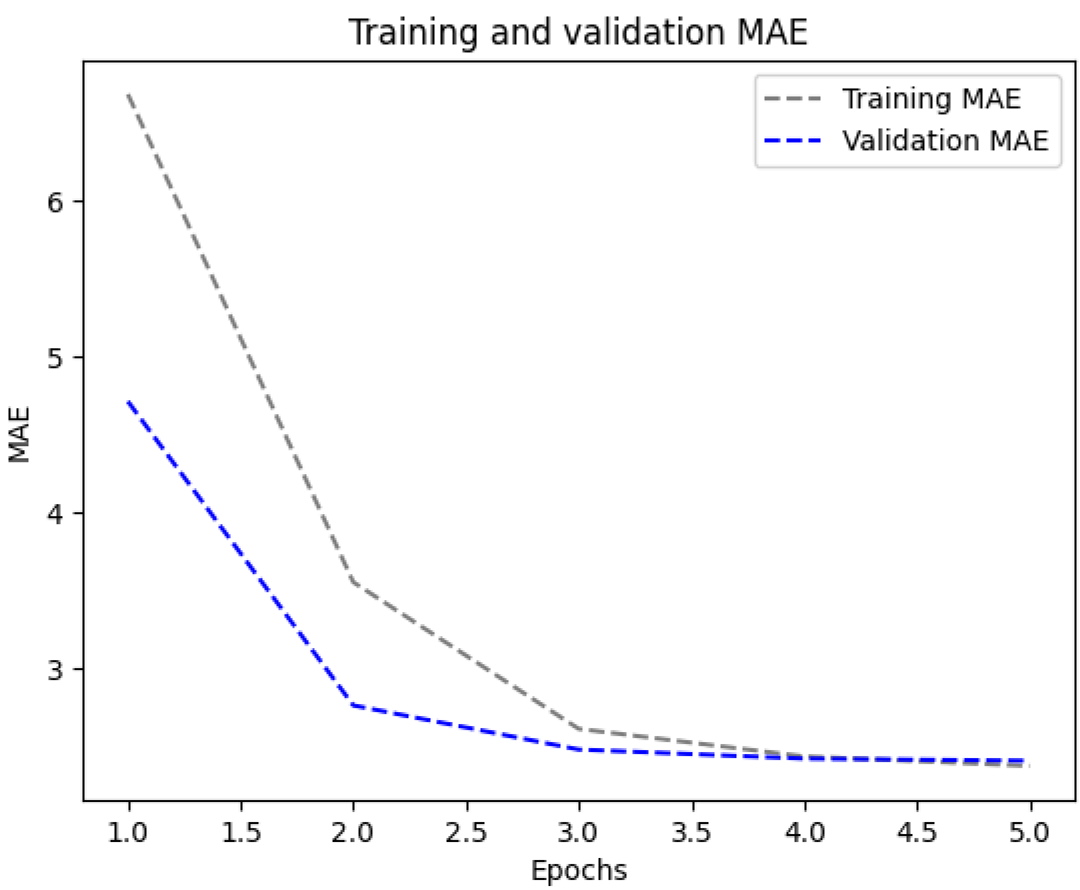
```
=] - 168s 199ms/step - loss: 75.3414 - mae: 6.6791 - val_loss: 39.8268 - val_mae: 4.7129

=] - 167s 204ms/step - loss: 23.3653 - mae: 3.5553 - val_loss: 13.8140 - val_mae: 2.7665

=] - 169s 206ms/step - loss: 11.4668 - mae: 2.6160 - val_loss: 10.4425 - val_mae: 2.4838
```

```
=] - 163s 198ms/step - loss: 9.8009 - mae: 2.4396 - val_loss: 9.8096 - val_mae: 2.4257

=] - 166s 203ms/step - loss: 9.3328 - mae: 2.3790 - val_loss: 9.6865 - val_mae: 2.4121
```

```
model_8u = keras.models.load_model("jena_LSTM_stacked3.keras")
print(f"Test MAE: {model_8u.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 34s 80ms/step - loss: 10.5611 - mae: 2.5446
Test MAE: 2.54
```

```
import matplotlib.pyplot as plt
loss_8u = history_8u.history["mae"]
validation_loss_8u = history_8u.history["val_mae"]

epochs = range(1, len(loss_8u) + 1)
plt.figure()
plt.plot(epochs, loss_8u, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_8u, color="blue",linestyle="dashed", label="Validation MAE
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



6.LSTM - dropout-regularized, stacked model

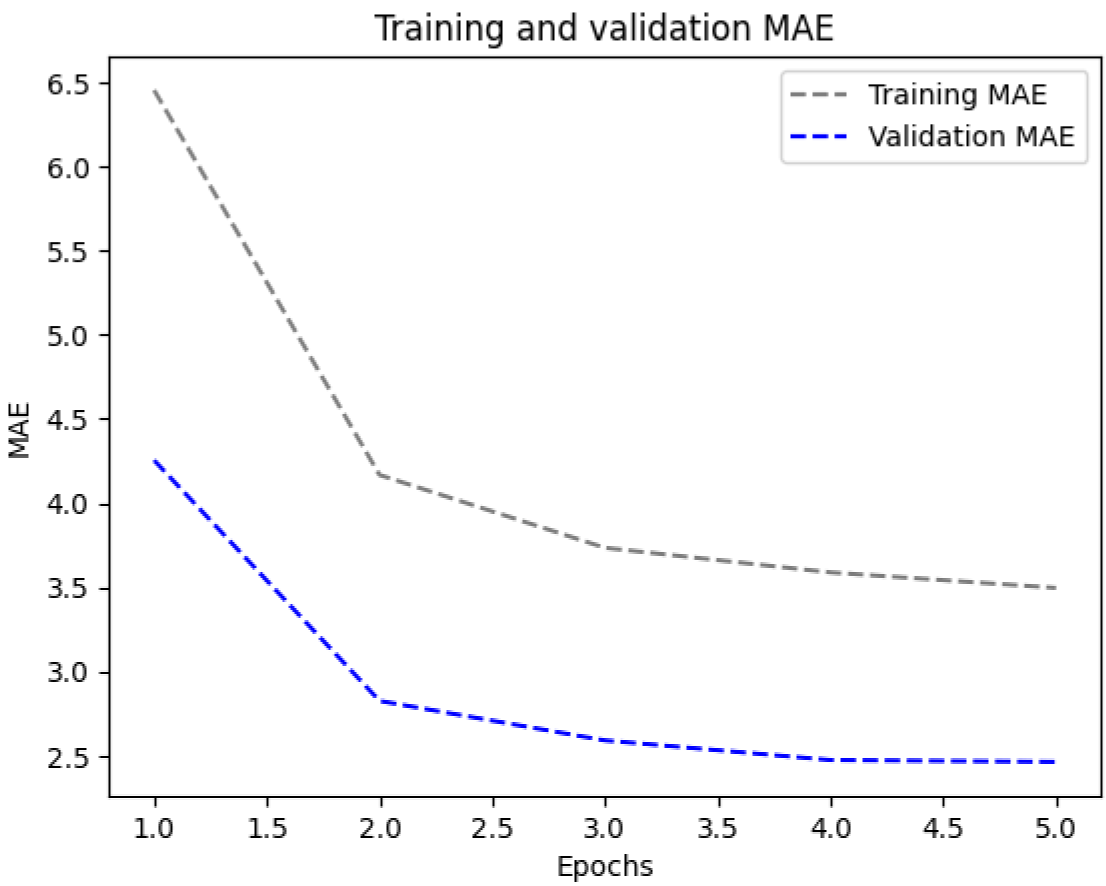
```
inputs = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
i = layers.LSTM(8, recurrent_dropout=0.5, return_sequences=True)(inputs)
i = layers.LSTM(8, recurrent_dropout=0.5)(i)
i = layers.Dropout(0.5)(i)
outputs = layers.Dense(1)(i)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_stacked_LSTM_dropout.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
=] - 298s 357ms/step - loss: 70.8341 - mae: 6.4512 - val_loss: 33.1843 - val_mae: 4.2534

=] - 282s 343ms/step - loss: 31.1402 - mae: 4.1663 - val_loss: 14.1205 - val_mae: 2.8257

=] - 282s 344ms/step - loss: 24.3762 - mae: 3.7338 - val_loss: 11.3885 - val_mae: 2.5912

=] - 293s 357ms/step - loss: 22.3891 - mae: 3.5878 - val_loss: 10.2776 - val_mae: 2.4750

=] - 283s 345ms/step - loss: 21.2213 - mae: 3.4963 - val_loss: 10.0852 - val_mae: 2.4643
```

```
model_r = keras.models.load_model("jena_stacked_LSTM_dropout.keras")
print(f"Test MAE: {model_r.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 38s 92ms/step - loss: 11.5611 - mae: 2.6300
Test MAE: 2.63
```

```
import matplotlib.pyplot as plt
loss_r = history.history["mae"]
validation_loss_r = history.history["val_mae"]

epochs = range(1, len(loss_r) + 1)
plt.figure()
plt.plot(epochs, loss_r, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_r, color="blue",linestyle="dashed", label="Validation MAE"
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



Bidirectional LSTM

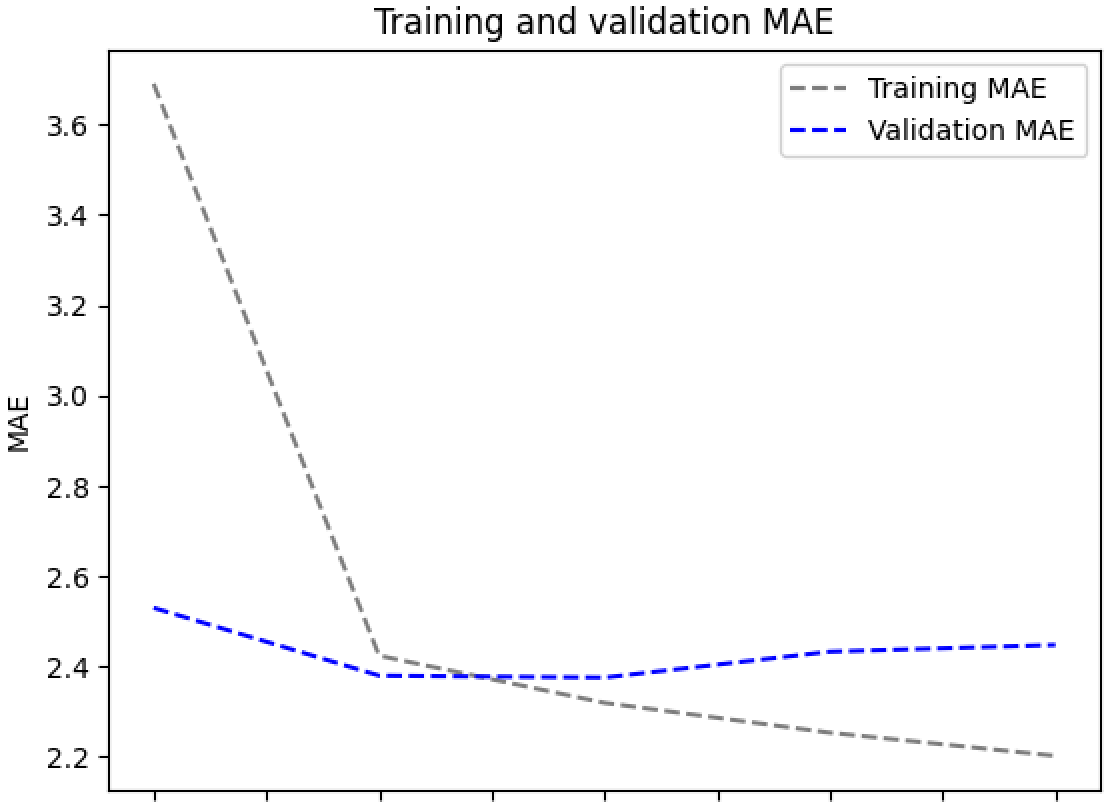
```
inputs = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_bidirec_LSTM.keras",
                                    save_best_only=True)
]

model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history.bi = model.fit(training_data,
                    epochs=5,
                    validation_data=validation_data,
                     callbacks=callbacks)
```

```
=] - 182s 215ms/step - loss: 26.2527 - mae: 3.6902 - val_loss: 10.6478 - val_mae: 2.5292

=] - 175s 213ms/step - loss: 9.6476 - mae: 2.4232 - val_loss: 9.5732 - val_mae: 2.3790

=] - 173s 211ms/step - loss: 8.8768 - mae: 2.3187 - val_loss: 9.5497 - val_mae: 2.3747

=] - 183s 222ms/step - loss: 8.3790 - mae: 2.2525 - val_loss: 9.8705 - val_mae: 2.4321

=] - 174s 212ms/step - loss: 7.9895 - mae: 2.2013 - val_loss: 10.1077 - val_mae: 2.4470
```

```
model_bi = keras.models.load_model("jena_bidirec_LSTM.keras")
print(f"Test MAE: {model_bi.evaluate(testing_data)[1]:.2f}")
```

```
405/405 [==============================] - 36s 85ms/step - loss: 10.1580 - mae: 2.5069
Test MAE: 2.51
```

```
import matplotlib.pyplot as plt
loss_bi = history.bi.history["mae"]
validation_loss_bi = history.bi.history["val_mae"]

epochs = range(1, len(loss_bi) + 1)
plt.figure()
plt.plot(epochs, loss_bi, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs,  validation_loss_bi, color="blue",linestyle="dashed", label="Validation MAE
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



1D Convnets and LSTM togther

```
input_final = keras.Input(shape=(sequencelength, raw_d.shape[-1]))
l = layers.Conv1D(64, 3, activation='relu')(input_final)
l = layers.MaxPooling1D(3)(l)
l = layers.Conv1D(128, 3, activation='relu')(l)
l = layers.GlobalMaxPooling1D()(l)
l = layers.Reshape((-1, 128))(l)  # Reshape the data to be 3D
l = layers.LSTM(16)(l)
output_final = layers.Dense(1)(l)
model_final = keras.Model(input_final, output_final)

model_final.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_Conv_LSTM.keras", save_best_only=True)
]

history_final = model_final.fit(training_data, epochs=5, validation_data=validation_data, ca
```

```
=] - 136s 162ms/step - loss: 46.8331 - mae: 5.1126 - val_loss: 25.6545 - val_mae: 3.9195

=] - 130s 158ms/step - loss: 17.3885 - mae: 3.2279 - val_loss: 23.7813 - val_mae: 3.8362

=] - 129s 157ms/step - loss: 14.3491 - mae: 2.9393 - val_loss: 25.5126 - val_mae: 3.9770

=] - 131s 159ms/step - loss: 12.6512 - mae: 2.7518 - val_loss: 26.2255 - val_mae: 4.1048
```