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

```
--2024-11-05 06:03:01--  https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
Resolving s3.amazonaws.com (s3.amazonaws.com)... 16.182.37.32, 52.217.124.168, 52.216.212.248, ...
Connecting to s3.amazonaws.com (s3.amazonaws.com)|16.182.37.32|: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  6.82MB/s    in 1.9s

2024-11-05 06:03:04 (6.82 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
```

Analysis of the Jena weather dataset, which contains 15 features and 420451 rows

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

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

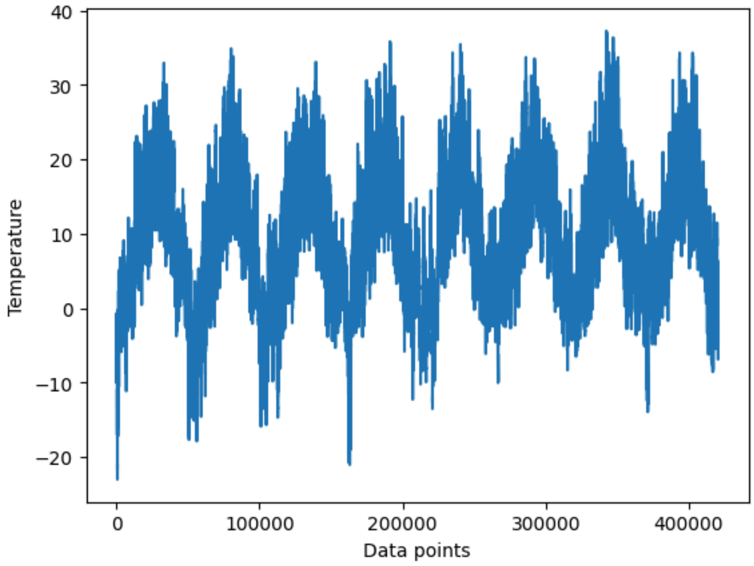
Specific values are stored in the temperature and raw_data arrays for further processing or analysis after data analysis. Values with commas are converted to floating-point numbers.

```
import numpy as np
temp1 = np.zeros((len(line1),))
rawdata1 = 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]
    rawdata1[i, :] = values[:]
```

The temperature timeseries plot

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

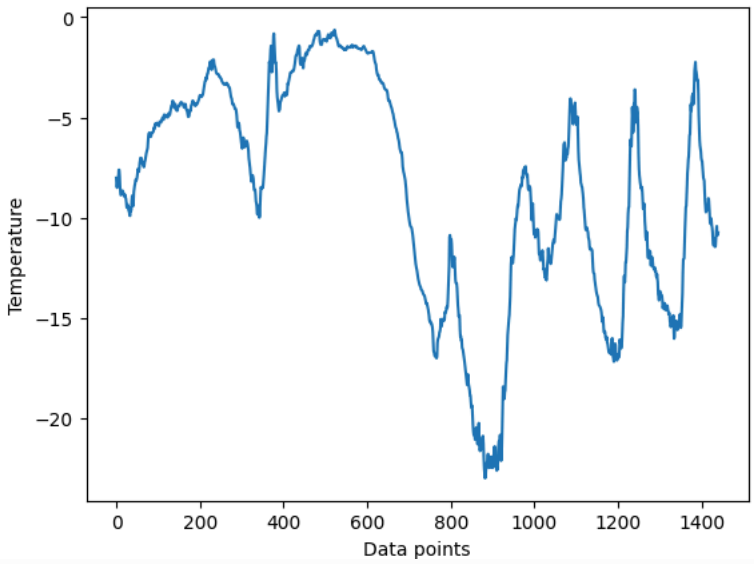
```
Text(0, 0.5, 'Temperature')
```



For the first ten days, the temperature time series is plotted. Since 144 data points are collected in a single day, ten days will yield 1440 data points.

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

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



Figuring out how many samples we'll need for each data split (train = 50%, validation = 25%).

```
num_of_train = int(0.5 * len(rawdata1))
num_of_validation= int(0.25 * len(rawdata1))
num_of_test= len(rawdata1) - num_of_train - num_of_validation
print("Number of train samples:", num_of_train)
print("Number of validation samples:", num_of_validation)
print("Number of test samples:", num_of_test)
```

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

Preparing the data

Data normalisation: Vectorisation is not required because the data is already numerically represented. All variables should be standardised, however, because the data scales are different—temperature ranges from -20 to +30, and pressure is measured in millibars.

```
mean1 = rawdata1[:num_of_train].mean(axis=0)
rawdata1 -= mean1
```

```
std = rawdata1[:num_of_train].std(axis=0)
rawdata1 /= std


import numpy as np
from tensorflow import keras
int_sequence1 = np.arange(10)
dummy_dataset1 = 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_dataset1:
    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
```

The development of training, validation, and testing datasets is crucial because to the substantial amount of duplication in the dataset's sample. It would be inefficient to explicitly allocate RAM for every sample. Rather, real-time sample generation will be used.

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

training_data = keras.utils.timeseries_dataset_from_array(
    rawdata1[:-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(
    rawdata1[:-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_validation)

testing_data = keras.utils.timeseries_dataset_from_array(
    rawdata1[:-delay],
    targets=temp1[delay:],
    sampling_rate=sample_rate,
    sequence_length=sequencelength,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_of_train + num_of_validation)
```

Generating the output of one of this datasets

```
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 common-sense, non-machine-learning baseline

Finding the baseline of common sense MAE: The "evaluate_naive_method" function lays the groundwork for assessing the effectiveness of a straightforward forecasting technique that uses the last value in the input sequence to predict the value that will follow a given value.

```
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
```

Predicting that the temperature will be the same 24 hours from now is a Common sense basilne approach. The validation mean absolute error (MAE) is 2.44 degrees Celsius whereas the test mean is 2.62 degrees Celsius utilizing this simple baseline. Stated otherwise, there would be an average variance of around 2.5 degrees if the future temperature were constant with the present one.

A basic machine-learning model - Dense Layer

Training and evaluating a densely connected model

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

inputs = keras.Input(shape=(sequencelength, rawdata1.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=20,
                    validation_data = validation_data, callbacks=callbacks)
```

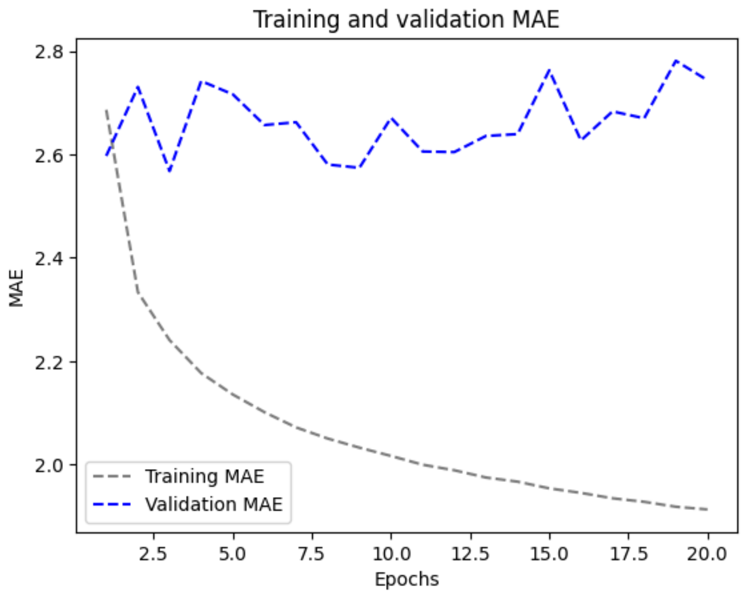
```
Epoch 1/20
819/819 [==============================] - 14s 16ms/step - loss: 12.0452 - mae: 2.6865 - val_loss: 10.8068 - val_mae: 2.5974
Epoch 2/20
819/819 [==============================] - 13s 16ms/step - loss: 8.7845 - mae: 2.3336 - val_loss: 11.8494 - val_mae: 2.7309
Epoch 3/20
819/819 [==============================] - 13s 16ms/step - loss: 8.0781 - mae: 2.2408 - val_loss: 10.5347 - val_mae: 2.5680
Epoch 4/20
819/819 [==============================] - 13s 16ms/step - loss: 7.6231 - mae: 2.1769 - val_loss: 11.9266 - val_mae: 2.7423
Epoch 5/20
819/819 [==============================] - 13s 16ms/step - loss: 7.3311 - mae: 2.1355 - val_loss: 11.6685 - val_mae: 2.7165
Epoch 6/20
819/819 [==============================] - 13s 16ms/step - loss: 7.0994 - mae: 2.1012 - val_loss: 11.1806 - val_mae: 2.6571
Epoch 7/20
819/819 [==============================] - 13s 16ms/step - loss: 6.8858 - mae: 2.0718 - val_loss: 11.3290 - val_mae: 2.6625
Epoch 8/20
819/819 [==============================] - 13s 16ms/step - loss: 6.7338 - mae: 2.0502 - val_loss: 10.5709 - val_mae: 2.5806
Epoch 9/20
819/819 [==============================] - 13s 16ms/step - loss: 6.6184 - mae: 2.0326 - val_loss: 10.6249 - val_mae: 2.5743
Epoch 10/20
819/819 [==============================] - 13s 16ms/step - loss: 6.5066 - mae: 2.0165 - val_loss: 11.4023 - val_mae: 2.6711
Epoch 11/20
819/819 [==============================] - 13s 16ms/step - loss: 6.3979 - mae: 1.9995 - val_loss: 10.8267 - val_mae: 2.6058
Epoch 12/20
819/819 [==============================] - 13s 16ms/step - loss: 6.3239 - mae: 1.9888 - val_loss: 10.8134 - val_mae: 2.6048
Epoch 13/20
819/819 [==============================] - 13s 16ms/step - loss: 6.2339 - mae: 1.9748 - val_loss: 11.0913 - val_mae: 2.6359
Epoch 14/20
819/819 [==============================] - 13s 16ms/step - loss: 6.1773 - mae: 1.9667 - val_loss: 11.1290 - val_mae: 2.6395
Epoch 15/20
819/819 [==============================] - 13s 16ms/step - loss: 6.1050 - mae: 1.9538 - val_loss: 12.1234 - val_mae: 2.7632
Epoch 16/20
819/819 [==============================] - 13s 15ms/step - loss: 6.0482 - mae: 1.9450 - val_loss: 11.0255 - val_mae: 2.6273
Epoch 17/20
819/819 [==============================] - 13s 16ms/step - loss: 5.9811 - mae: 1.9345 - val_loss: 11.4594 - val_mae: 2.6835
Epoch 18/20
819/819 [==============================] - 13s 15ms/step - loss: 5.9376 - mae: 1.9278 - val_loss: 11.3356 - val_mae: 2.6702
Epoch 19/20
819/819 [==============================] - 13s 15ms/step - loss: 5.8804 - mae: 1.9181 - val_loss: 12.2557 - val_mae: 2.7814
Epoch 20/20
```

```
819/819 [==============================] - 13s 16ms/step - loss: 5.8515 - mae: 1.9130 - val_loss: 11.9352 - val_mae: 2.7439
```

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

```
405/405 [==============================] - 4s 10ms/step - loss: 12.1246 - mae: 2.7338
Test MAE: 2.73
```

```
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()
```



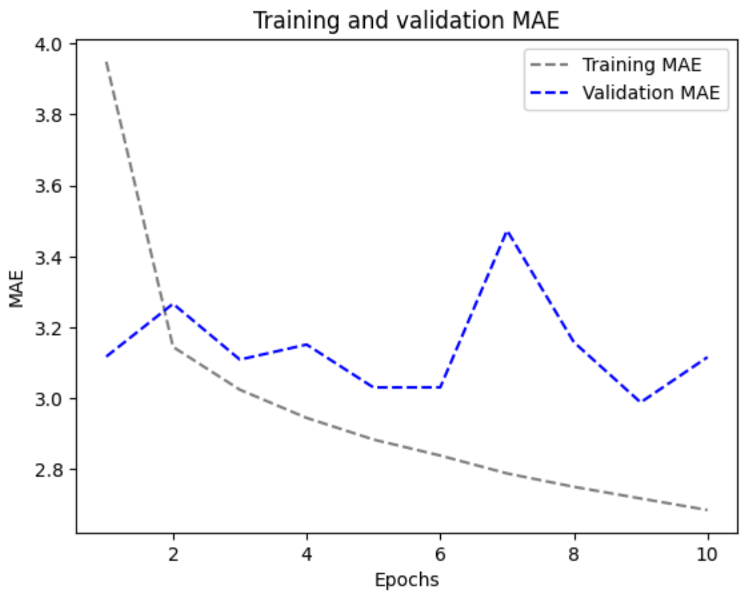
Let's try a 1D convolutional model

```
inputs = keras.Input(shape=(sequencelength, rawdata1.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=10,
                    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 1/10
819/819 [==============================] - 21s 25ms/step - loss: 26.4000 - mae: 3.9483 - val_loss: 16.0040 - val_mae: 3.1175
Epoch 2/10
819/819 [==============================] - 20s 25ms/step - loss: 15.7543 - mae: 3.1449 - val_loss: 16.8795 - val_mae: 3.2665
Epoch 3/10
819/819 [==============================] - 21s 25ms/step - loss: 14.5645 - mae: 3.0242 - val_loss: 15.7441 - val_mae: 3.1092
Epoch 4/10
819/819 [==============================] - 21s 25ms/step - loss: 13.8380 - mae: 2.9448 - val_loss: 16.0852 - val_mae: 3.1515
```

```
Epoch 5/10
819/819 [==============================] - 20s 25ms/step - loss: 13.2808 - mae: 2.8839 - val_loss: 14.7700 - val_mae: 3.0306
Epoch 6/10
819/819 [==============================] - 21s 25ms/step - loss: 12.8890 - mae: 2.8387 - val_loss: 14.7629 - val_mae: 3.0309
Epoch 7/10
819/819 [==============================] - 21s 26ms/step - loss: 12.4847 - mae: 2.7884 - val_loss: 18.6077 - val_mae: 3.4733
Epoch 8/10
819/819 [==============================] - 21s 25ms/step - loss: 12.1737 - mae: 2.7506 - val_loss: 16.0350 - val_mae: 3.1582
Epoch 9/10
819/819 [==============================] - 21s 26ms/step - loss: 11.8842 - mae: 2.7178 - val_loss: 14.5850 - val_mae: 2.9885
Epoch 10/10
819/819 [==============================] - 21s 26ms/step - loss: 11.6132 - mae: 2.6853 - val_loss: 15.8397 - val_mae: 3.1161
405/405 [==============================] - 5s 12ms/step - loss: 16.8583 - mae: 3.2897
Test MAE: 3.29
```

```
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()
```



Dense models or common sense seem to outperform convolutional data. That might be because of

Weather data does not conform to the translation invariance assumption. The order in which the information is provided is crucial. Recent past data is notably more beneficial than data acquired many days in advance when it comes to predicting the temperature for the next day. Sadly, a 1D convolutional neural network is not able to adequately represent this significant temporal order.

A Simple RNN

1.An RNN layer that can process 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,
                    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 [==============================] - 22s 26ms/step - loss: 138.6124 - mae: 9.6757 - val_loss: 143.9894 - val_mae: 9.8919
Epoch 2/5
819/819 [==============================] - 21s 25ms/step - loss: 136.4758 - mae: 9.5652 - val_loss: 143.8651 - val_mae: 9.8868
Epoch 3/5
819/819 [==============================] - 20s 25ms/step - loss: 136.3643 - mae: 9.5570 - val_loss: 143.6878 - val_mae: 9.8661
Epoch 4/5
819/819 [==============================] - 21s 25ms/step - loss: 136.2702 - mae: 9.5464 - val_loss: 143.7424 - val_mae: 9.8729
Epoch 5/5
819/819 [==============================] - 21s 26ms/step - loss: 136.2361 - mae: 9.5439 - val_loss: 143.6123 - val_mae: 9.8584
405/405 [==============================] - 5s 12ms/step - loss: 151.3971 - mae: 9.9304
Test MAE: 9.93
```

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 [==============================] - 59s 70ms/step - loss: 136.8174 - mae: 9.5662 - val_loss: 143.4155 - val_mae: 9.8356
Epoch 2/5
819/819 [==============================] - 57s 69ms/step - loss: 135.9528 - mae: 9.5124 - val_loss: 143.4041 - val_mae: 9.8340
Epoch 3/5
819/819 [==============================] - 57s 69ms/step - loss: 135.9112 - mae: 9.5070 - val_loss: 143.4544 - val_mae: 9.8432
Epoch 4/5
819/819 [==============================] - 57s 69ms/step - loss: 135.8887 - mae: 9.5045 - val_loss: 143.3970 - val_mae: 9.8317
Epoch 5/5
819/819 [==============================] - 57s 69ms/step - loss: 135.8791 - mae: 9.5040 - val_loss: 143.4372 - val_mae: 9.8376
405/405 [==============================] - 9s 21ms/step - loss: 151.1318 - mae: 9.9070
Test MAE: 9.91
```

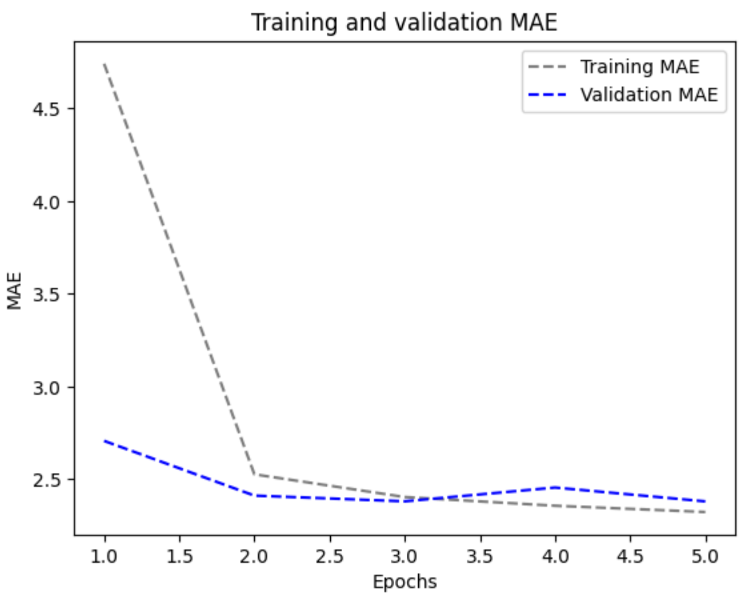
A Simple GRU (Gated Recurrent Unit)

```
inputs_GRU = keras.Input(shape=(sequencelength, rawdata1.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 [==============================] - 46s 54ms/step - loss: 42.5877 - mae: 4.7406 - val_loss: 12.9575 - val_mae: 2.7068
Epoch 2/5
819/819 [==============================] - 44s 54ms/step - loss: 10.5300 - mae: 2.5264 - val_loss: 9.9407 - val_mae: 2.4117
Epoch 3/5
819/819 [==============================] - 44s 54ms/step - loss: 9.4840 - mae: 2.4039 - val_loss: 9.7019 - val_mae: 2.3808
Epoch 4/5
819/819 [==============================] - 45s 54ms/step - loss: 9.1298 - mae: 2.3570 - val_loss: 10.6240 - val_mae: 2.4552
```

```
Epoch 5/5
819/819 [==============================] - 45s 54ms/step - loss: 8.8541 - mae: 2.3232 - val_loss: 9.7072 - val_mae: 2.3805
405/405 [==============================] - 7s 17ms/step - loss: 10.0502 - mae: 2.4868
Test MAE: 2.49
```

```
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 MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



LSTM(Long Short-Term Memory)

1.LSTM-Simple

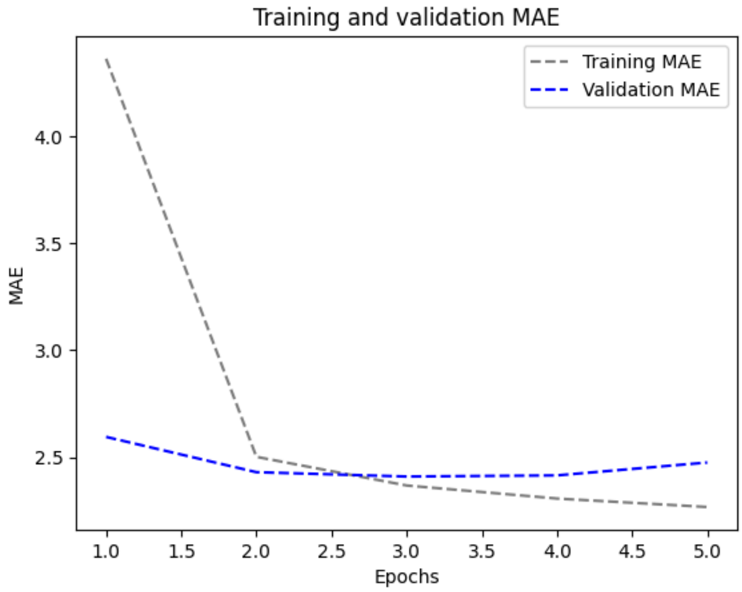
```
inputs_LSTMS = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
c = layers.LSTM(16)(inputs_LSTMS)
output_LSTMS = layers.Dense(1)(c)
model_LSTMS = keras.Model(inputs_LSTMS, output_LSTMS)

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 [==============================] - 51s 60ms/step - loss: 36.2371 - mae: 4.3624 - val_loss: 11.4865 - val_mae: 2.5950
Epoch 2/5
819/819 [==============================] - 47s 57ms/step - loss: 10.3823 - mae: 2.5019 - val_loss: 9.7631 - val_mae: 2.4301
Epoch 3/5
819/819 [==============================] - 48s 58ms/step - loss: 9.2574 - mae: 2.3679 - val_loss: 9.5843 - val_mae: 2.4098
Epoch 4/5
819/819 [==============================] - 48s 58ms/step - loss: 8.7810 - mae: 2.3069 - val_loss: 9.7165 - val_mae: 2.4152
Epoch 5/5
819/819 [==============================] - 47s 57ms/step - loss: 8.4589 - mae: 2.2674 - val_loss: 9.9850 - val_mae: 2.4754
```

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

```
405/405 [==============================] - 9s 22ms/step - loss: 11.3230 - mae: 2.6185
Test MAE: 2.62
```

```
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 MAE")
plt.plot(epochs,  validation_loss_LSTMS, color="blue",linestyle="dashed", label="Validation MAE")
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, rawdata1.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)
```

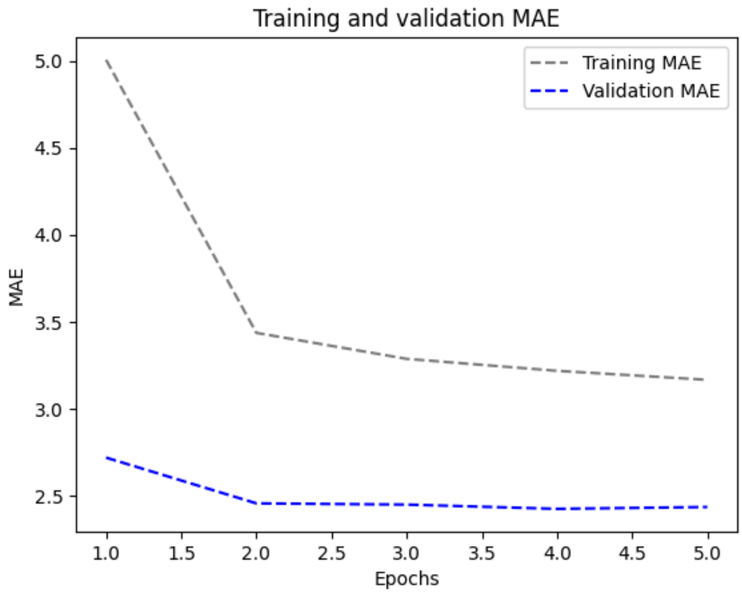
```
Epoch 1/5
819/819 [==============================] - 63s 74ms/step - loss: 45.0087 - mae: 5.0057 - val_loss: 12.9218 - val_mae: 2.7177
Epoch 2/5
819/819 [==============================] - 61s 75ms/step - loss: 19.9979 - mae: 3.4353 - val_loss: 9.9902 - val_mae: 2.4546
Epoch 3/5
819/819 [==============================] - 61s 74ms/step - loss: 18.2268 - mae: 3.2857 - val_loss: 9.8223 - val_mae: 2.4475
Epoch 4/5
819/819 [==============================] - 60s 74ms/step - loss: 17.4911 - mae: 3.2170 - val_loss: 9.6533 - val_mae: 2.4230
Epoch 5/5
819/819 [==============================] - 61s 75ms/step - loss: 16.9608 - mae: 3.1652 - val_loss: 9.7137 - val_mae: 2.4336
```

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

```
405/405 [==============================] - 7s 18ms/step - loss: 11.3158 - mae: 2.6440
Test MAE: 2.64
```

```
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 MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



3.LSTM - Stacked setup with 16 units

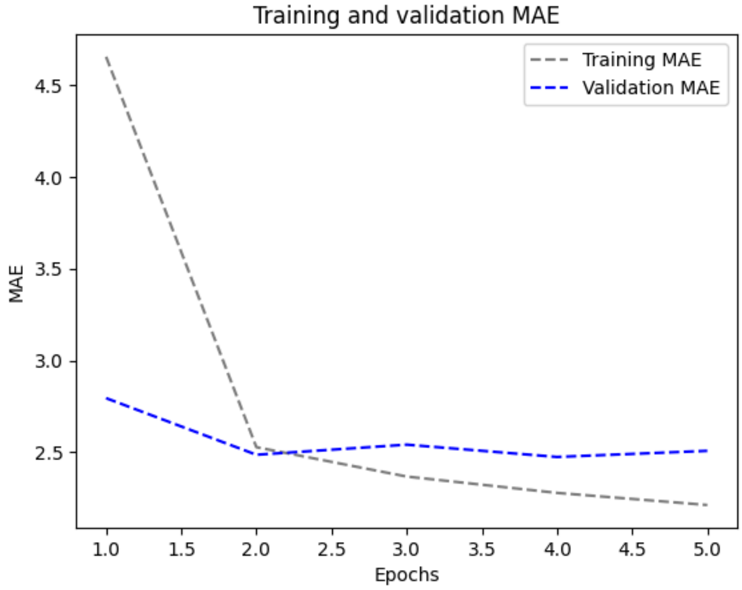
```
input_16 = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
e = layers.LSTM(16, return_sequences=True)(input_16)
e = layers.LSTM(16)(e)
output_16 = layers.Dense(1)(e)
model_16 = keras.Model(input_16, output_16)

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)
```

```
Epoch 1/5
819/819 [==============================] - 95s 112ms/step - loss: 40.7777 - mae: 4.6530 - val_loss: 13.7474 - val_mae: 2.7951
Epoch 2/5
819/819 [==============================] - 91s 111ms/step - loss: 10.5412 - mae: 2.5283 - val_loss: 10.3929 - val_mae: 2.4870
Epoch 3/5
819/819 [==============================] - 91s 112ms/step - loss: 9.2325 - mae: 2.3684 - val_loss: 10.9594 - val_mae: 2.5420
Epoch 4/5
819/819 [==============================] - 93s 113ms/step - loss: 8.5649 - mae: 2.2795 - val_loss: 10.3091 - val_mae: 2.4750
Epoch 5/5
819/819 [==============================] - 98s 120ms/step - loss: 8.0894 - mae: 2.2136 - val_loss: 10.7779 - val_mae: 2.5083
```

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

```
405/405 [==============================] - 18s 43ms/step - loss: 10.8945 - mae: 2.5739
Test MAE: 2.57
```

```
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

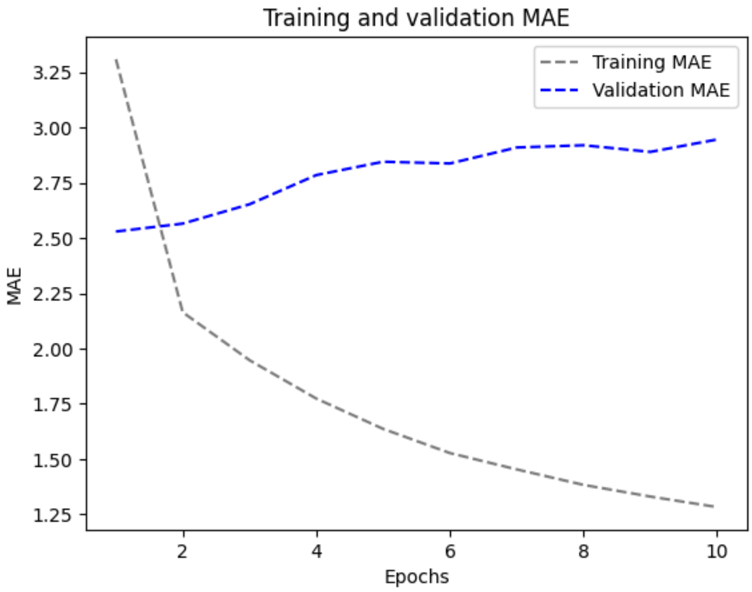
```
input_32 = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
f = layers.LSTM(32, return_sequences=True)(input_32)
f = layers.LSTM(32)(f)
output_32 = layers.Dense(1)(f)
model_32 = keras.Model(input_32, output_32)

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=10,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
Epoch 1/10
819/819 [==============================] - 135s 161ms/step - loss: 21.3956 - mae: 3.3080 - val_loss: 10.6142 - val_mae: 2.5291
Epoch 2/10
819/819 [==============================] - 133s 163ms/step - loss: 7.7380 - mae: 2.1641 - val_loss: 10.6745 - val_mae: 2.5648
Epoch 3/10
819/819 [==============================] - 131s 159ms/step - loss: 6.3248 - mae: 1.9475 - val_loss: 11.3574 - val_mae: 2.6522
Epoch 4/10
819/819 [==============================] - 132s 161ms/step - loss: 5.2764 - mae: 1.7738 - val_loss: 12.6916 - val_mae: 2.7843
Epoch 5/10
819/819 [==============================] - 131s 160ms/step - loss: 4.5091 - mae: 1.6370 - val_loss: 13.0164 - val_mae: 2.8446
Epoch 6/10
819/819 [==============================] - 131s 160ms/step - loss: 3.9636 - mae: 1.5276 - val_loss: 13.2187 - val_mae: 2.8367
Epoch 7/10
819/819 [==============================] - 131s 160ms/step - loss: 3.6076 - mae: 1.4539 - val_loss: 13.6979 - val_mae: 2.9090
Epoch 8/10
819/819 [==============================] - 131s 160ms/step - loss: 3.2690 - mae: 1.3838 - val_loss: 13.9185 - val_mae: 2.9191
Epoch 9/10
819/819 [==============================] - 132s 161ms/step - loss: 3.0368 - mae: 1.3310 - val_loss: 13.6088 - val_mae: 2.8890
Epoch 10/10
819/819 [==============================] - 132s 161ms/step - loss: 2.8350 - mae: 1.2835 - val_loss: 14.1639 - val_mae: 2.9452
```

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

```
405/405 [==============================] - 25s 60ms/step - loss: 11.8499 - mae: 2.6846
Test MAE: 2.68
```

```
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

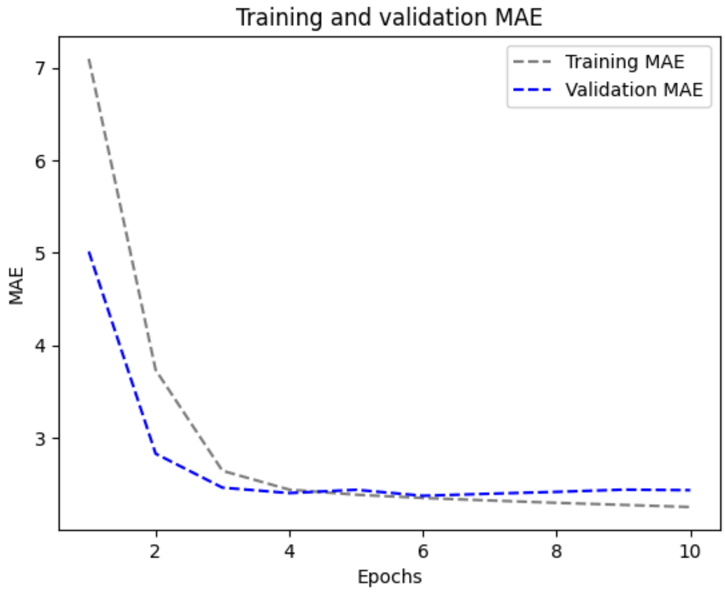
```
input_8u = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
h = layers.LSTM(8, return_sequences=True)(input_8u)
h = layers.LSTM(8)(h)
output_8u = layers.Dense(1)(h)
model_8u = keras.Model(input_8u, output_8u)

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=10,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

```
Epoch 1/10
819/819 [==============================] - 80s 94ms/step - loss: 83.6946 - mae: 7.0961 - val_loss: 44.6675 - val_mae: 5.0133
Epoch 2/10
819/819 [==============================] - 76s 93ms/step - loss: 25.9108 - mae: 3.7350 - val_loss: 14.6795 - val_mae: 2.8299
Epoch 3/10
819/819 [==============================] - 76s 93ms/step - loss: 11.8872 - mae: 2.6448 - val_loss: 10.2768 - val_mae: 2.4627
Epoch 4/10
819/819 [==============================] - 75s 92ms/step - loss: 9.8301 - mae: 2.4411 - val_loss: 9.6133 - val_mae: 2.4042
Epoch 5/10
819/819 [==============================] - 76s 93ms/step - loss: 9.3754 - mae: 2.3865 - val_loss: 9.8600 - val_mae: 2.4397
Epoch 6/10
819/819 [==============================] - 75s 92ms/step - loss: 9.0854 - mae: 2.3511 - val_loss: 9.4056 - val_mae: 2.3749
Epoch 7/10
819/819 [==============================] - 76s 93ms/step - loss: 8.8377 - mae: 2.3241 - val_loss: 9.5384 - val_mae: 2.3971
Epoch 8/10
819/819 [==============================] - 75s 91ms/step - loss: 8.6360 - mae: 2.2987 - val_loss: 9.6933 - val_mae: 2.4173
Epoch 9/10
819/819 [==============================] - 76s 92ms/step - loss: 8.4587 - mae: 2.2763 - val_loss: 9.8581 - val_mae: 2.4411
Epoch 10/10
819/819 [==============================] - 75s 91ms/step - loss: 8.2919 - mae: 2.2536 - val_loss: 9.8433 - val_mae: 2.4355
```

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

```
405/405 [==============================] - 13s 31ms/step - loss: 10.5655 - mae: 2.5485
Test MAE: 2.55
```

```
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, rawdata1.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=10,
                    validation_data=validation_data,
                    callbacks=callbacks)
```

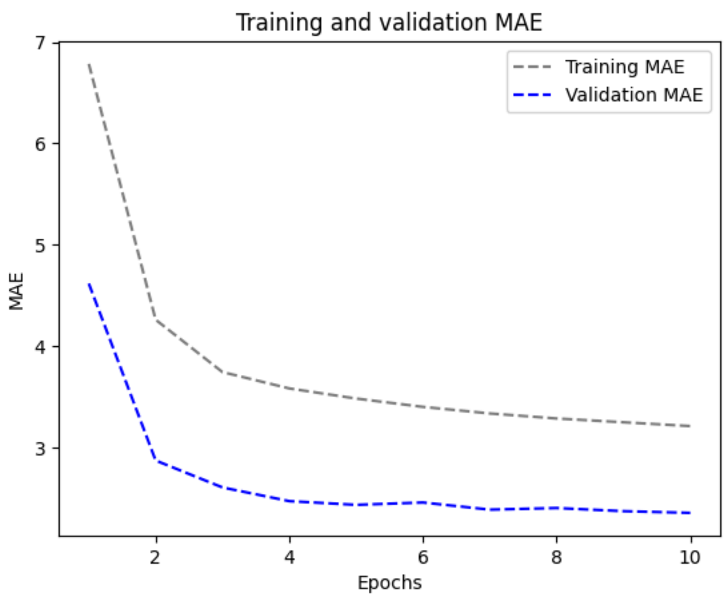
```
Epoch 1/10
819/819 [==============================] - 111s 131ms/step - loss: 77.4515 - mae: 6.7849 - val_loss: 38.3474 - val_mae: 4.6167
Epoch 2/10
819/819 [==============================] - 106s 130ms/step - loss: 32.7173 - mae: 4.2595 - val_loss: 14.7777 - val_mae: 2.8700
Epoch 3/10
819/819 [==============================] - 107s 131ms/step - loss: 24.5228 - mae: 3.7427 - val_loss: 11.5339 - val_mae: 2.6041
Epoch 4/10
819/819 [==============================] - 107s 130ms/step - loss: 22.3103 - mae: 3.5812 - val_loss: 10.2491 - val_mae: 2.4688
Epoch 5/10
819/819 [==============================] - 107s 130ms/step - loss: 21.0526 - mae: 3.4813 - val_loss: 9.8957 - val_mae: 2.4321
Epoch 6/10
819/819 [==============================] - 107s 130ms/step - loss: 20.0226 - mae: 3.3992 - val_loss: 10.0048 - val_mae: 2.4553
Epoch 7/10
819/819 [==============================] - 107s 130ms/step - loss: 19.2403 - mae: 3.3342 - val_loss: 9.4321 - val_mae: 2.3849
Epoch 8/10
819/819 [==============================] - 107s 130ms/step - loss: 18.6343 - mae: 3.2845 - val_loss: 9.5767 - val_mae: 2.4008
Epoch 9/10
819/819 [==============================] - 107s 130ms/step - loss: 18.1585 - mae: 3.2472 - val_loss: 9.3525 - val_mae: 2.3697
```

```
Epoch 10/10
819/819 [==============================] - 107s 131ms/step - loss: 17.7361 - mae: 3.2096 - val_loss: 9.1938 - val_mae: 2.3531
```

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

```
405/405 [==============================] - 12s 28ms/step - loss: 10.7076 - mae: 2.5495
Test MAE: 2.55
```

```
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

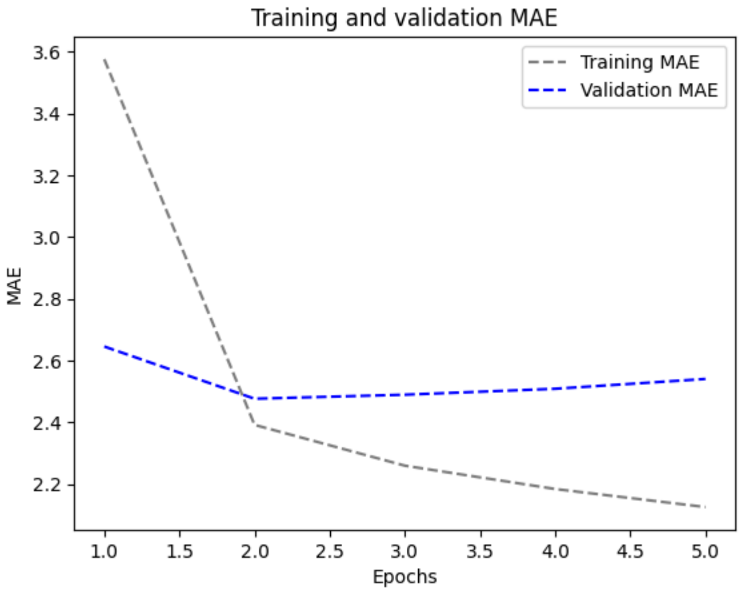
```
inputs = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
x = layers.Bidirectional(layers.LSTM(16))(inputs)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

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)
```

```
Epoch 1/5
819/819 [==============================] - 55s 63ms/step - loss: 24.2825 - mae: 3.5753 - val_loss: 11.6624 - val_mae: 2.6455
Epoch 2/5
819/819 [==============================] - 51s 63ms/step - loss: 9.4036 - mae: 2.3918 - val_loss: 10.2716 - val_mae: 2.4764
Epoch 3/5
819/819 [==============================] - 52s 63ms/step - loss: 8.4239 - mae: 2.2597 - val_loss: 10.3157 - val_mae: 2.4895
Epoch 4/5
819/819 [==============================] - 51s 62ms/step - loss: 7.8794 - mae: 2.1842 - val_loss: 10.5304 - val_mae: 2.5087
Epoch 5/5
819/819 [==============================] - 51s 63ms/step - loss: 7.4591 - mae: 2.1257 - val_loss: 10.8015 - val_mae: 2.5404
```

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

```
405/405 [==============================] - 11s 26ms/step - loss: 10.7618 - mae: 2.5669
Test MAE: 2.57
```

```
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

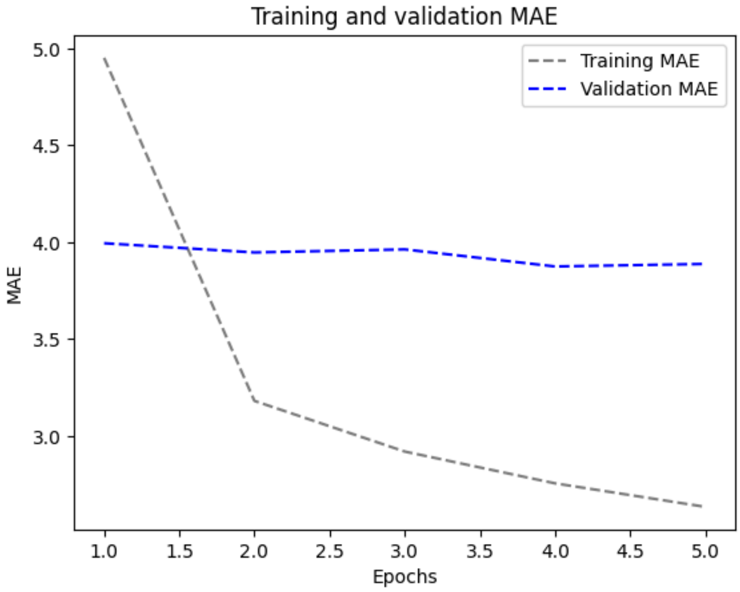
```
input_final = keras.Input(shape=(sequencelength, rawdata1.shape[-1]))
l = layers.Conv1D(64, 3, activation='relu')(input_final)
l = layers.MaxPooling1D(3)(l)
l = layers.Conv1D(128, 3, activation='relu')(l)
l = layers.GlobalMaxPooling1D()(l)
l = layers.Reshape((-1, 128))(l)  # Reshape the data to be 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, callbacks=callbacks)
```

```
Epoch 1/5
819/819 [==============================] - 32s 36ms/step - loss: 43.9835 - mae: 4.9519 - val_loss: 26.7604 - val_mae: 3.9949
Epoch 2/5
819/819 [==============================] - 29s 35ms/step - loss: 16.9126 - mae: 3.1812 - val_loss: 25.4092 - val_mae: 3.9474
Epoch 3/5
819/819 [==============================] - 29s 35ms/step - loss: 14.1405 - mae: 2.9196 - val_loss: 24.8320 - val_mae: 3.9632
Epoch 4/5
819/819 [==============================] - 29s 35ms/step - loss: 12.6689 - mae: 2.7555 - val_loss: 24.0716 - val_mae: 3.8751
Epoch 5/5
819/819 [==============================] - 29s 35ms/step - loss: 11.6056 - mae: 2.6340 - val_loss: 23.6682 - val_mae: 3.8880
```

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

```
405/405 [==============================] - 6s 14ms/step - loss: 23.4822 - mae: 3.8894
Test MAE: 3.89
```

```
import matplotlib.pyplot as plt
loss_final = history_final.history["mae"]
validation_loss_final = history_final.history["val_mae"]

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



Built 14 models: Following are the details;

Model 1: common-sense, non-machine-learning baseline

Model 2: A basic machine-learning model

Model 3: 1D convolutional model

Model 4: Simple RNN layer that can process sequences of any length

Model 5: Simple RNN - Stacking RNN layers

Model 6: A Simple GRU (Gated Recurrent Unit)

Model 7: LSTM-Simple

Model 8: LSTM - dropout Regularization

Model 9: Stacked setup with 16 units

Model 10: Stacked setup with 32 units

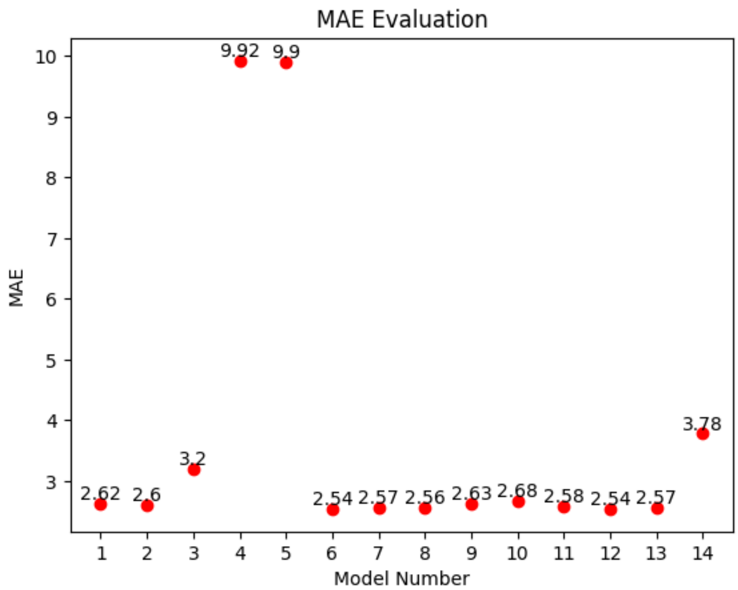
Model 11: Stacked setup with 8 units

Model 12: LSTM - dropout-regularized, stacked

Model 13: Bidirectional LSTM

Model 14: 1D Convnets and LSTM togther

```
Models = ("1","2","3","4","5","6","7","8","9","10","11","12","13","14")
Mae = (2.62,2.60,3.2,9.92,9.9,2.54,2.57,2.56,2.63,2.68,2.58,2.54,2.57,3.78)

# MAE Evaluation
plt.scatter(Models, Mae, color="red")
plt.title("MAE Evaluation")
plt.xlabel("Model Number")
plt.ylabel("MAE")

for (xi, yi) in zip(Models,Mae):
    plt.text(xi, yi, yi, va='bottom', ha='center')

plt.show()
```




```
!jupyter nbconvert --to html /content/Assignment_Time_Series_Data.ipynb
```

```
[NbConvertApp] WARNING | pattern '/content/Assignment_Time_Series_Data.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.

        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and include the error message in the cell output (the de
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
```