

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

```
Requirement already satisfied: tensorflow==2.12 in /usr/local/lib/python3.11/dist-packages (2.12.0)
Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.6.3)
Requirement already satisfied: flatbuffers>=2.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (25.2.10)
Requirement already satisfied: gast<0.4.0,>=0.2.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (0.4.0)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (0.2.0)
Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.71.0)
Requirement already satisfied: h5py>=2.9.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (3.13.0)
Requirement already satisfied: jax>=0.3.15 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (0.4.30)
Requirement already satisfied: keras<2.13,>=2.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (2.12.0)
Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (18.1.1)
Requirement already satisfied: numpy<1.24,>=1.22 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.23.5)
Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (3.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (24.2)
Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (75.2.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.17.0)
Requirement already satisfied: tensorboard<2.13,>=2.12 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (2.12.3)
Requirement already satisfied: tensorflow-estimator<2.13,>=2.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (2.12.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (3.0.1)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (4.13.0)
Requirement already satisfied: wrapt<1.15,>=1.11.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (1.14.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow==2.12) (0.37.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow==2.12) (0.43.0)
Requirement already satisfied: jaxlib<0.4.30,>=0.4.27 in /usr/local/lib/python3.11/dist-packages (from jax>=0.3.15->tensorflow==2.12) (0.4.30)
Requirement already satisfied: ml-dtypes>=0.2.0 in /usr/local/lib/python3.11/dist-packages (from jax>=0.3.15->tensorflow==2.12) (0.4.0)
Requirement already satisfied: scipy>=1.9 in /usr/local/lib/python3.11/dist-packages (from jax>=0.3.15->tensorflow==2.12) (1.14.1)
Requirement already satisfied: google-auth<3,>=1.6.3 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (2.36.0)
Requirement already satisfied: google-auth-oauthlib<1.1,>=0.5 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (1.0.0)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (3.7.0)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (2.32.3)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (0.17.0)
Requirement already satisfied: werkzeug>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.13,>=2.12->tensorflow==2.12) (3.0.6)
Requirement already satisfied: cachetools<6.0,>=2.0.0 in /usr/local/lib/python3.11/dist-packages (from google-auth<3,>=1.6.3->tensorflow==2.12) (5.5.2)
Requirement already satisfied: pyasn1-modules>=0.2.1 in /usr/local/lib/python3.11/dist-packages (from google-auth<3,>=1.6.3->tensorflow==2.12) (0.6.1)
Requirement already satisfied: rsa<5,>=3.1.4 in /usr/local/lib/python3.11/dist-packages (from google-auth<3,>=1.6.3->tensorflow==2.12) (4.9)
Requirement already satisfied: requests-oauthlib>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from google-auth-oauthlib<1.1,>=0.5->tensorflow==2.12) (2.0.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow==2.12) (3.4.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow==2.12) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow==2.12) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow==2.12) (2025.1.31)
Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorflow==2.12) (3.0.2)
Requirement already satisfied: pyasn1<0.7.0,>=0.6.1 in /usr/local/lib/python3.11/dist-packages (from pyasn1-modules>=0.2.1->tensorflow==2.12) (0.6.1)
Requirement already satisfied: oauthlib>=3.0.0 in /usr/local/lib/python3.11/dist-packages (from requests-oauthlib>=0.7.0->tensorflow==2.12) (3.2.2)
```

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

```
!unzip jena_climate_2009_2016.csv.zip
```

```
--2025-04-05 02:45:36-- https://s3.amazonaws.com/keras-datasets/jena_climate_2009_2016.csv.zip
Resolving s3.amazonaws.com (s3.amazonaws.com)... 3.5.24.152, 52.217.159.40, 54.231.236.176, ...
Connecting to s3.amazonaws.com (s3.amazonaws.com)|3.5.24.152|: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 60.6MB/s in 0.2s
```

```
2025-04-05 02:45:36 (60.6 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
```

## ✓ Loading and inspecting the jena climate dataset

```
import os
```

```
file_name = os.path.join("jena_climate_2009_2016.csv")
with open(file_name) as file:
    content = file.read()
```

```
line_list = content.split("\n")
header_columns = line_list[0].split(",")
line_list = line_list[1:]
```

```
print(header_columns)
print(f"Number of data lines: {len(line_list)}")
```

```
variable_count = len(header_columns)
```

```
print(f"Total variables: {variable_count}")
row_count = len(line_list)
print(f"Total data rows: {row_count}")
```

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

```
import numpy as np
```

```
temp_values = np.zeros((len(lines),))
dataset = np.zeros((len(lines), len(header) - 1))
```

```
for index, line in enumerate(lines):
    values = [float(x) for x in line.split(",")[1:]]
    temp_values[index] = values[1]
    dataset[index, :] = values[:]
```

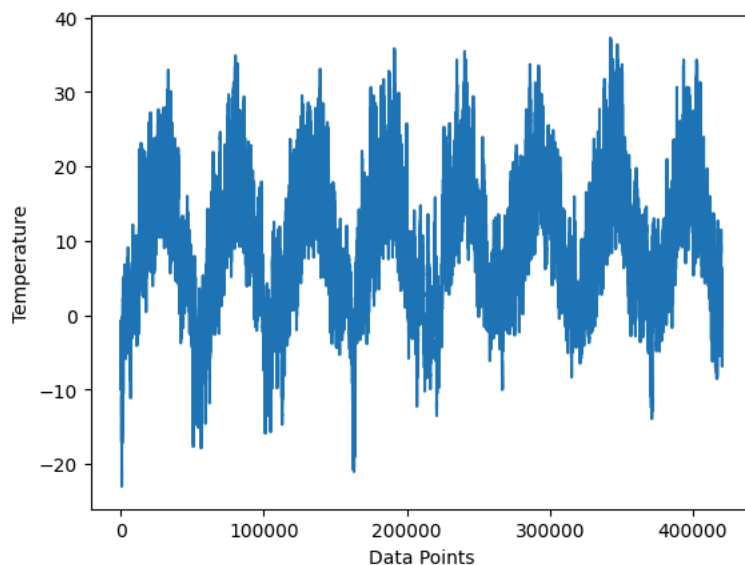
## ✓ Plotting the Temperature Data

```
from matplotlib import pyplot as plt
```

```
plt.plot(range(len(temp_values)), temp_values)
```

```
plt.xlabel('Data Points')
plt.ylabel('Temperature')
```

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

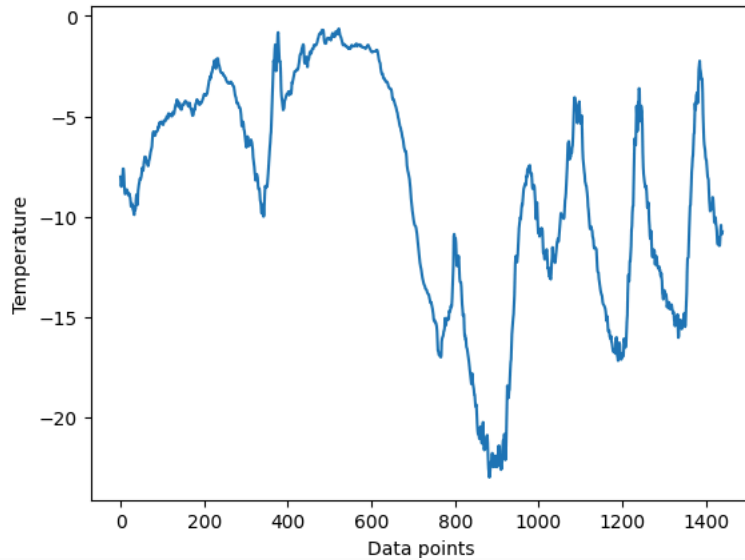


## ✓ # Plotting the First 1440 Data Points of Temperature

```
plt.plot(range(1440), temperature[:1440])
```

```
plt.xlabel('Data Points')
plt.ylabel('Temperature')
```

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



## ✓ Split the data into Training, Validation, and Test Sets

```
num_train_samples = int(0.5 * len(raw_data))
num_val_samples = int(0.25 * len(raw_data))
num_test_samples = len(raw_data) - num_train_samples - num_val_samples

print("num_train_samples:", num_train_samples)
print("num_val_samples:", num_val_samples)
print("num_test_samples:", num_test_samples)
```

```
num_train_samples: 210225
num_val_samples: 105112
num_test_samples: 105114
```

## ✓ Normalization of the dataset

```
mean = raw_data[:num_train_samples].mean(axis=0)
raw_data -= mean
std = raw_data[:num_train_samples].std(axis=0)
raw_data /= std
```

```
import numpy as np
from tensorflow import keras
```

```
# Create a simple sequence
int_sequence = np.arange(10)
```

```
# Create a timeseries dataset
dummy_dataset = keras.utils.timeseries_dataset_from_array(
    data=int_sequence[:-3],
    targets=int_sequence[3:],
    sequence_length=3,
    batch_size=2,
)
```

```
# Print the data in the dataset
for inputs, targets in dummy_dataset:
    print("Inputs:", inputs.numpy())
    print("Targets:", targets.numpy())
```

```
Inputs: [[0 1 2]
 [1 2 3]]
Targets: [3 4]
Inputs: [[2 3 4]
 [3 4 5]]
Targets: [5 6]
Inputs: [[4 5 6]]
```

Targets: [7]

- Because of extremely redundant samples, datasets for training, validation, and
- ✓ testing must be created. Creating samples dynamically is more economical than explicitly allocating RAM for each one.

```
sampling_rate = 6
sequence_length = 120
delay = sampling_rate * (sequence_length + 24 - 1)
batch_size = 256

train_dataset = keras.utils.timeseries_dataset_from_array(
    raw_data[:-delay],
    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(
    raw_data[:-delay],
    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(
    raw_data[:-delay],
    targets=temperature[delay:],
    sampling_rate=sampling_rate,
    sequence_length=sequence_length,
    shuffle=True,
    batch_size=batch_size,
    start_index=num_train_samples + num_val_samples)
```

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

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

- ✓ Using Naive Method to evaluate on Validation and Test Datasets

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

print(f"Validation MAE: {evaluate_naive_method(val_dataset):.2f}")
print(f"Test MAE: {evaluate_naive_method(test_dataset):.2f}")
```

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

- ✓ A Simple Machine Learning Model

## Training a Densely Connected Model with Dense Layers

```

from tensorflow import keras
from tensorflow.keras import layers

inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Flatten()(inputs)
x = layers.Dense(16, activation="relu")(x)
outputs = layers.Dense(1)(x)
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(train_dataset, epochs=10,
                    validation_data=val_dataset, callbacks=callbacks)

```

Epoch 1/10  
819/819 [=====] - 39s 46ms/step - loss: 11.7600 - mae: 2.6677 - val\_loss: 11.0277 - val\_mae: 2.6082  
Epoch 2/10  
819/819 [=====] - 38s 46ms/step - loss: 8.9924 - mae: 2.3609 - val\_loss: 10.2216 - val\_mae: 2.5111  
Epoch 3/10  
819/819 [=====] - 39s 47ms/step - loss: 8.2312 - mae: 2.2587 - val\_loss: 10.3483 - val\_mae: 2.5376  
Epoch 4/10  
819/819 [=====] - 37s 45ms/step - loss: 7.7807 - mae: 2.1965 - val\_loss: 10.4877 - val\_mae: 2.5588  
Epoch 5/10  
819/819 [=====] - 38s 46ms/step - loss: 7.4456 - mae: 2.1481 - val\_loss: 10.5028 - val\_mae: 2.5491  
Epoch 6/10  
819/819 [=====] - 38s 46ms/step - loss: 7.2002 - mae: 2.1114 - val\_loss: 10.5866 - val\_mae: 2.5556  
Epoch 7/10  
819/819 [=====] - 39s 47ms/step - loss: 7.0036 - mae: 2.0838 - val\_loss: 10.9655 - val\_mae: 2.6026  
Epoch 8/10  
819/819 [=====] - 38s 46ms/step - loss: 6.8299 - mae: 2.0586 - val\_loss: 12.6466 - val\_mae: 2.8241  
Epoch 9/10  
819/819 [=====] - 37s 45ms/step - loss: 6.6728 - mae: 2.0348 - val\_loss: 12.3689 - val\_mae: 2.7842  
Epoch 10/10  
819/819 [=====] - 40s 49ms/step - loss: 6.5558 - mae: 2.0157 - val\_loss: 11.5414 - val\_mae: 2.6915

```

trained_model = keras.models.load_model("jena_dense.keras")
test_loss, test_mae = trained_model.evaluate(test_dataset)
print(f"Test MAE: {test_mae:.2f}")

```

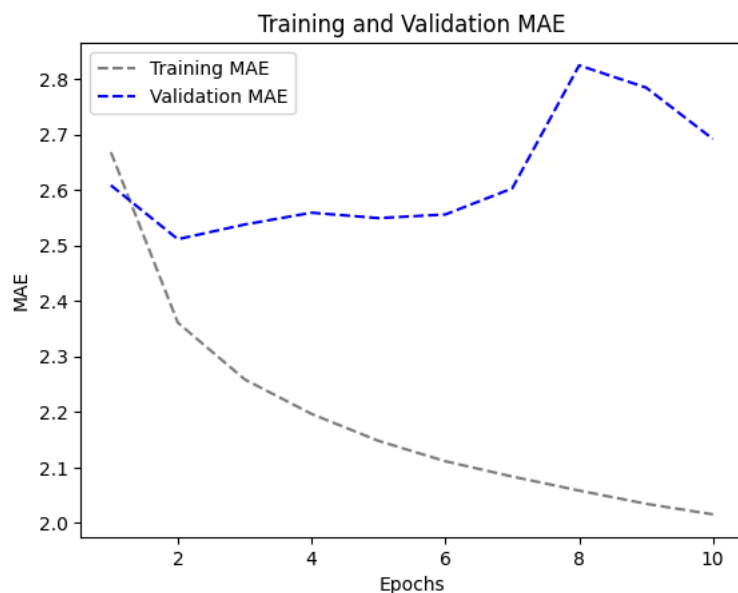
405/405 [=====] - 13s 31ms/step - loss: 11.5259 - mae: 2.6621  
Test MAE: 2.66

```

import matplotlib.pyplot as plt
train_mae = history.history["mae"]
val_mae = history.history["val_mae"]

epochs = range(1, len(train_mae) + 1)
plt.figure()
plt.plot(epochs, train_mae, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs, val_mae, 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=(sequence_length, raw_data.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)
conv_model = keras.Model(inputs, outputs)

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

conv_model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
train_history = conv_model.fit(train_dataset,
                               epochs=10,
                               validation_data=val_dataset,
                               callbacks=callbacks)

conv_model = keras.models.load_model("jena_conv_model.keras")
test_mae = conv_model.evaluate(test_dataset)[1]
print(f"Test MAE: {test_mae:.2f}")
```



```
Epoch 1/10
819/819 [=====] - 76s 91ms/step - loss: 21.2280 - mae: 3.6357 - val_loss: 15.7119 - val_mae: 3.1604
Epoch 2/10
819/819 [=====] - 73s 89ms/step - loss: 15.8685 - mae: 3.1692 - val_loss: 15.5528 - val_mae: 3.1152
Epoch 3/10
819/819 [=====] - 73s 89ms/step - loss: 14.5882 - mae: 3.0308 - val_loss: 16.5856 - val_mae: 3.2163
Epoch 4/10
819/819 [=====] - 74s 90ms/step - loss: 13.7942 - mae: 2.9467 - val_loss: 14.6970 - val_mae: 3.0323
Epoch 5/10
819/819 [=====] - 77s 94ms/step - loss: 13.2162 - mae: 2.8806 - val_loss: 14.3100 - val_mae: 2.9816
Epoch 6/10
819/819 [=====] - 73s 89ms/step - loss: 12.7732 - mae: 2.8303 - val_loss: 14.8865 - val_mae: 3.0267
Epoch 7/10
819/819 [=====] - 74s 90ms/step - loss: 12.3294 - mae: 2.7770 - val_loss: 19.8827 - val_mae: 3.5551
Epoch 8/10
819/819 [=====] - 72s 88ms/step - loss: 11.9288 - mae: 2.7304 - val_loss: 13.5676 - val_mae: 2.8793
Epoch 9/10
819/819 [=====] - 76s 93ms/step - loss: 11.5674 - mae: 2.6866 - val_loss: 14.0109 - val_mae: 2.9308
Epoch 10/10
819/819 [=====] - 75s 91ms/step - loss: 11.2272 - mae: 2.6446 - val_loss: 16.5856 - val_mae: 3.2106
405/405 [=====] - 16s 38ms/step - loss: 15.6721 - mae: 3.1254
Test MAE: 3.13
```

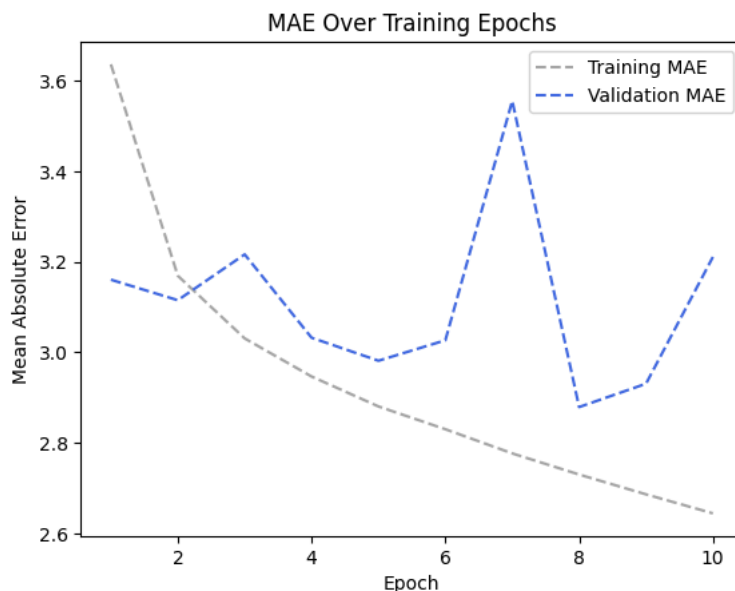
```
import matplotlib.pyplot as plt
```

```
train_mae = train_history.history["mae"]
val_mae = train_history.history["val_mae"]
```

```

epoch_range = range(1, len(train_mae) + 1)
plt.figure()
plt.plot(epoch_range, train_mae, color="darkgray", linestyle="dashed", label="Training MAE")
plt.plot(epoch_range, val_mae, color="royalblue", linestyle="dashed", label="Validation MAE")
plt.title("MAE Over Training Epochs")
plt.xlabel("Epoch")
plt.ylabel("Mean Absolute Error")
plt.legend()
plt.show()

```



#### A Simple RNN

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

```

num_attributes = 14
rnn_input = keras.Input(shape=(None, num_attributes))
rnn_output = layers.SimpleRNN(16)(rnn_input)

rnn_model = keras.Model(rnn_input, rnn_output)

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

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

rnn_history = rnn_model.fit(
    train_dataset,
    epochs=10,
    validation_data=val_dataset,
    callbacks=rnn_callbacks
)

rnn_model = keras.models.load_model("jena_SimpleRNN.keras")
print(f"Test MAE: {rnn_model.evaluate(test_dataset)[1]:.2f}")

```



```

Epoch 1/10
819/819 [=====] - 59s 70ms/step - loss: 138.7691 - mae: 9.6853 - val_loss: 144.0174 - val_mae: 9.8998
Epoch 2/10
819/819 [=====] - 57s 69ms/step - loss: 136.4728 - mae: 9.5676 - val_loss: 143.7852 - val_mae: 9.8775
Epoch 3/10
819/819 [=====] - 63s 77ms/step - loss: 136.2807 - mae: 9.5524 - val_loss: 143.7764 - val_mae: 9.8768
Epoch 4/10
819/819 [=====] - 58s 70ms/step - loss: 136.2122 - mae: 9.5469 - val_loss: 143.6462 - val_mae: 9.8619
Epoch 5/10
819/819 [=====] - 56s 68ms/step - loss: 136.1657 - mae: 9.5429 - val_loss: 143.6396 - val_mae: 9.8626
Epoch 6/10
819/819 [=====] - 56s 68ms/step - loss: 136.1559 - mae: 9.5389 - val_loss: 143.5580 - val_mae: 9.8505
Epoch 7/10
819/819 [=====] - 56s 68ms/step - loss: 136.1321 - mae: 9.5349 - val_loss: 143.5320 - val_mae: 9.8492
Epoch 8/10
819/819 [=====] - 58s 70ms/step - loss: 136.1238 - mae: 9.5337 - val_loss: 143.5414 - val_mae: 9.8515
Epoch 9/10
819/819 [=====] - 57s 69ms/step - loss: 136.1084 - mae: 9.5319 - val_loss: 143.5318 - val_mae: 9.8494

```

```
Epoch 10/10
819/819 [=====] - 56s 68ms/step - loss: 136.1009 - mae: 9.5314 - val_loss: 143.5453 - val_mae: 9.8541
405/405 [=====] - 15s 35ms/step - loss: 151.2942 - mae: 9.9209
Test MAE: 9.92
```

## ✓ Simple GRU(Gated Recurrent Unit)-Based Forecasting Model

```
gru_input = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
gru_output = layers.GRU(16)(gru_input)
final_prediction = layers.Dense(1)(gru_output)

gru_model = keras.Model(gru_input, final_prediction)
++++
gru_callbacks = [
    keras.callbacks.ModelCheckpoint("jena_gru_revised.keras", save_best_only=True)
]

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

gru_history = gru_model.fit(
    train_dataset,
    epochs=10,
    validation_data=val_dataset,
    callbacks=gru_callbacks
)

gru_model = keras.models.load_model("jena_gru_revised.keras")
print(f"Test MAE: {gru_model.evaluate(test_dataset)[1]:.2f}")
```

```
↩ Epoch 1/10
819/819 [=====] - 89s 107ms/step - loss: 46.6345 - mae: 4.9659 - val_loss: 14.7772 - val_mae: 2.8809
Epoch 2/10
819/819 [=====] - 88s 107ms/step - loss: 11.0741 - mae: 2.5807 - val_loss: 10.2557 - val_mae: 2.4598
Epoch 3/10
819/819 [=====] - 93s 113ms/step - loss: 9.8941 - mae: 2.4538 - val_loss: 9.7186 - val_mae: 2.3971
Epoch 4/10
819/819 [=====] - 88s 107ms/step - loss: 9.6009 - mae: 2.4153 - val_loss: 10.4599 - val_mae: 2.4550
Epoch 5/10
819/819 [=====] - 89s 108ms/step - loss: 9.3397 - mae: 2.3831 - val_loss: 10.3195 - val_mae: 2.4421
Epoch 6/10
819/819 [=====] - 89s 109ms/step - loss: 9.0443 - mae: 2.3472 - val_loss: 10.5758 - val_mae: 2.4585
Epoch 7/10
819/819 [=====] - 90s 109ms/step - loss: 8.8426 - mae: 2.3226 - val_loss: 10.5224 - val_mae: 2.4505
Epoch 8/10
819/819 [=====] - 87s 106ms/step - loss: 8.6812 - mae: 2.3024 - val_loss: 10.5422 - val_mae: 2.4545
Epoch 9/10
819/819 [=====] - 86s 105ms/step - loss: 8.5186 - mae: 2.2819 - val_loss: 11.3468 - val_mae: 2.5309
Epoch 10/10
819/819 [=====] - 88s 108ms/step - loss: 8.3604 - mae: 2.2626 - val_loss: 10.7582 - val_mae: 2.4766
405/405 [=====] - 19s 44ms/step - loss: 10.7177 - mae: 2.5453
Test MAE: 2.55
```

## ✓ Using MAE to Visualize Training and Validation Across Epochs

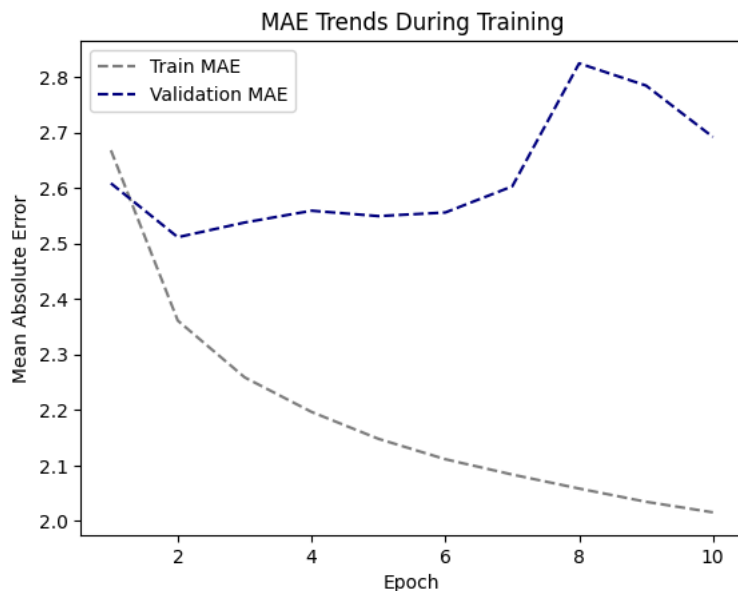
```
import matplotlib.pyplot as plt

train_mae = history.history["mae"]
val_mae = history.history["val_mae"]

epoch_range = range(1, len(train_mae) + 1)

plt.figure()
plt.plot(epoch_range, train_mae, linestyle="dashed", color="gray", label="Train MAE")
plt.plot(epoch_range, val_mae, linestyle="dashed", color="navy", label="Validation MAE")
plt.title("MAE Trends During Training")
plt.xlabel("Epoch")
plt.ylabel("Mean Absolute Error")
plt.legend()
plt.show()
```





## ✓ 1) Weather Forecasting Model Based on LSTM (Simple Variant)

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

input_layer = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
lstm_out = layers.LSTM(16)(input_layer)
final_output = layers.Dense(1)(lstm_out)

lstm_model = keras.Model(inputs=input_layer, outputs=final_output)

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

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

history = lstm_model.fit(
    train_dataset,
    epochs=10,
    validation_data=val_dataset,
    callbacks=model_callbacks
)

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



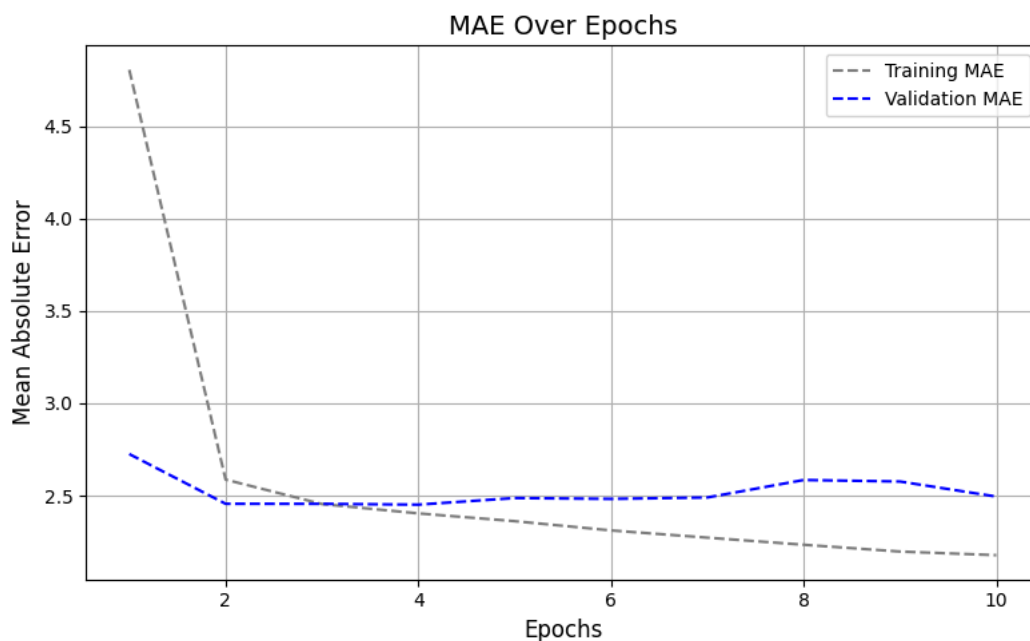
```
Epoch 1/10
819/819 [=====] - 91s 109ms/step - loss: 43.5690 - mae: 4.8067 - val_loss: 13.0324 - val_mae: 2.7253
Epoch 2/10
819/819 [=====] - 89s 108ms/step - loss: 11.1094 - mae: 2.5868 - val_loss: 9.9978 - val_mae: 2.4557
Epoch 3/10
819/819 [=====] - 88s 107ms/step - loss: 9.8949 - mae: 2.4544 - val_loss: 10.2412 - val_mae: 2.4555
Epoch 4/10
819/819 [=====] - 85s 103ms/step - loss: 9.4806 - mae: 2.4038 - val_loss: 10.1890 - val_mae: 2.4511
Epoch 5/10
819/819 [=====] - 91s 110ms/step - loss: 9.1455 - mae: 2.3616 - val_loss: 10.4434 - val_mae: 2.4868
Epoch 6/10
819/819 [=====] - 90s 109ms/step - loss: 8.7237 - mae: 2.3115 - val_loss: 10.3291 - val_mae: 2.4823
Epoch 7/10
819/819 [=====] - 87s 106ms/step - loss: 8.4383 - mae: 2.2724 - val_loss: 10.3054 - val_mae: 2.4898
Epoch 8/10
819/819 [=====] - 87s 106ms/step - loss: 8.1511 - mae: 2.2339 - val_loss: 12.1899 - val_mae: 2.5847
Epoch 9/10
819/819 [=====] - 86s 105ms/step - loss: 7.9208 - mae: 2.1970 - val_loss: 11.4212 - val_mae: 2.5764
Epoch 10/10
819/819 [=====] - 87s 106ms/step - loss: 7.7719 - mae: 2.1774 - val_loss: 10.3366 - val_mae: 2.4949
405/405 [=====] - 20s 49ms/step - loss: 12.2512 - mae: 2.6543
Test MAE: 2.65
```

## ✓ Comparing Training and Validation MAE Visualization

```
import matplotlib.pyplot as plt

train_mae = history.history["mae"]
val_mae = history.history["val_mae"]
epoch_range = range(1, len(train_mae) + 1)

plt.figure(figsize=(8, 5))
plt.plot(epoch_range, train_mae, linestyle="--", color="gray", label="Training MAE")
plt.plot(epoch_range, val_mae, linestyle="--", color="blue", label="Validation MAE")
plt.title("MAE Over Epochs", fontsize=14)
plt.xlabel("Epochs", fontsize=12)
plt.ylabel("Mean Absolute Error", fontsize=12)
plt.legend()
plt.grid(True)
plt.tight_layout()
plt.show()
```



## 2) Implementing dropout regularization in the LSTM model definition

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

input_layer = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
lstm_layer = layers.LSTM(16, recurrent_dropout=0.25)(input_layer)
dropout_layer = layers.Dropout(0.5)(lstm_layer)
output_layer = layers.Dense(1)(dropout_layer)
model = keras.Model(inputs=input_layer, outputs=output_layer)

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

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

history = model.fit(
    train_dataset,
    epochs=10,
    validation_data=val_dataset,
    callbacks=callbacks
)

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

Epoch 1/10  
 819/819 [=====] - 142s 170ms/step - loss: 48.4423 - mae: 5.1821 - val\_loss: 13.4173 - val\_mae: 2.7666  
 Epoch 2/10  
 819/819 [=====] - 139s 169ms/step - loss: 20.1722 - mae: 3.4476 - val\_loss: 9.8401 - val\_mae: 2.4416  
 Epoch 3/10  
 819/819 [=====] - 139s 170ms/step - loss: 18.1262 - mae: 3.2763 - val\_loss: 9.9156 - val\_mae: 2.4568

```

Epoch 4/10
819/819 [=====] - 138s 168ms/step - loss: 17.2891 - mae: 3.2031 - val_loss: 9.5551 - val_mae: 2.4100
Epoch 5/10
819/819 [=====] - 138s 168ms/step - loss: 16.5836 - mae: 3.1363 - val_loss: 9.4817 - val_mae: 2.3962
Epoch 6/10
819/819 [=====] - 136s 166ms/step - loss: 15.9493 - mae: 3.0794 - val_loss: 9.2660 - val_mae: 2.3662
Epoch 7/10
819/819 [=====] - 136s 166ms/step - loss: 15.4179 - mae: 3.0269 - val_loss: 9.4775 - val_mae: 2.3986
Epoch 8/10
819/819 [=====] - 138s 168ms/step - loss: 15.0649 - mae: 2.9935 - val_loss: 9.2954 - val_mae: 2.3759
Epoch 9/10
819/819 [=====] - 135s 165ms/step - loss: 14.7115 - mae: 2.9636 - val_loss: 9.2114 - val_mae: 2.3601
Epoch 10/10
819/819 [=====] - 134s 163ms/step - loss: 14.5888 - mae: 2.9502 - val_loss: 9.2604 - val_mae: 2.3637
405/405 [=====] - 21s 51ms/step - loss: 10.5127 - mae: 2.5661
Test MAE: 2.57

```

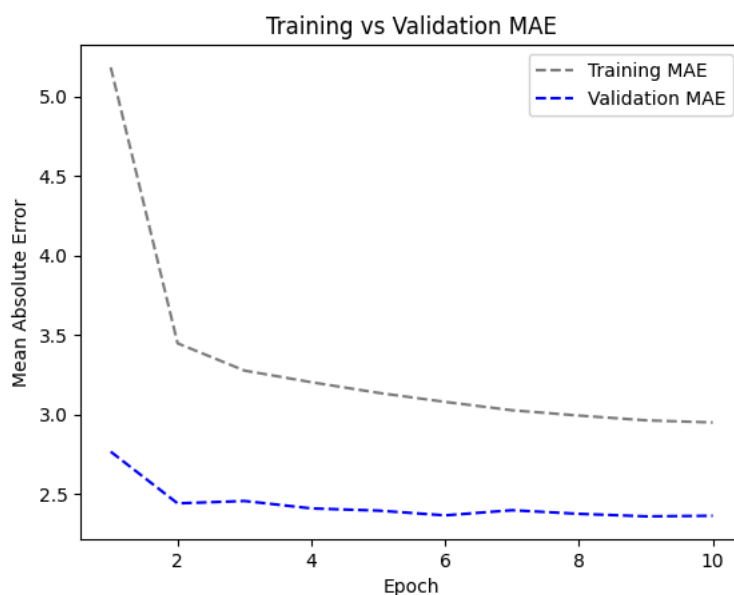
```
import matplotlib.pyplot as plt
```

```
train_mae = history.history["mae"]
val_mae = history.history["val_mae"]
```

```

epoch_range = range(1, len(train_mae) + 1)
plt.figure()
plt.plot(epoch_range, train_mae, linestyle="dashed", color="grey", label="Training MAE")
plt.plot(epoch_range, val_mae, linestyle="dashed", color="blue", label="Validation MAE")
plt.title("Training vs Validation MAE")
plt.xlabel("Epoch")
plt.ylabel("Mean Absolute Error")
plt.legend()
plt.show()

```



### ✓ 3)Implementing dropout regularization in the LSTM model definition

```

from tensorflow import keras
from tensorflow.keras import layers

input_layer = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
lstm_out = layers.LSTM(16, return_sequences=True)(input_layer)
lstm_out = layers.LSTM(16)(lstm_out)
final_output = layers.Dense(1)(lstm_out)

model = keras.Model(input_layer, final_output)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked1.keras", save_best_only=True)
]

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

history = model.fit(
    train_dataset,
    epochs=10,
    validation_data=val_dataset,

```

```

callbacks=callbacks
)

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

Epoch 1/10
819/819 [=====] - 152s 181ms/step - loss: 35.0749 - mae: 4.3104 - val_loss: 11.9298 - val_mae: 2.6442
Epoch 2/10
819/819 [=====] - 148s 180ms/step - loss: 10.1062 - mae: 2.4756 - val_loss: 10.1021 - val_mae: 2.4830
Epoch 3/10
819/819 [=====] - 144s 175ms/step - loss: 8.8632 - mae: 2.3302 - val_loss: 10.1888 - val_mae: 2.4610
Epoch 4/10
819/819 [=====] - 146s 178ms/step - loss: 8.1260 - mae: 2.2324 - val_loss: 11.1643 - val_mae: 2.5963
Epoch 5/10
819/819 [=====] - 143s 175ms/step - loss: 7.5157 - mae: 2.1468 - val_loss: 10.9523 - val_mae: 2.5597
Epoch 6/10
819/819 [=====] - 147s 179ms/step - loss: 7.1268 - mae: 2.0855 - val_loss: 11.3259 - val_mae: 2.6079
Epoch 7/10
819/819 [=====] - 149s 181ms/step - loss: 6.7092 - mae: 2.0259 - val_loss: 11.7375 - val_mae: 2.6825
Epoch 8/10
819/819 [=====] - 147s 179ms/step - loss: 6.4212 - mae: 1.9813 - val_loss: 11.8019 - val_mae: 2.6570
Epoch 9/10
819/819 [=====] - 145s 177ms/step - loss: 6.1756 - mae: 1.9423 - val_loss: 12.4981 - val_mae: 2.7491
Epoch 10/10
819/819 [=====] - 145s 177ms/step - loss: 5.9162 - mae: 1.9002 - val_loss: 12.3592 - val_mae: 2.7265
405/405 [=====] - 29s 69ms/step - loss: 11.1604 - mae: 2.5971
Test MAE: 2.60

```

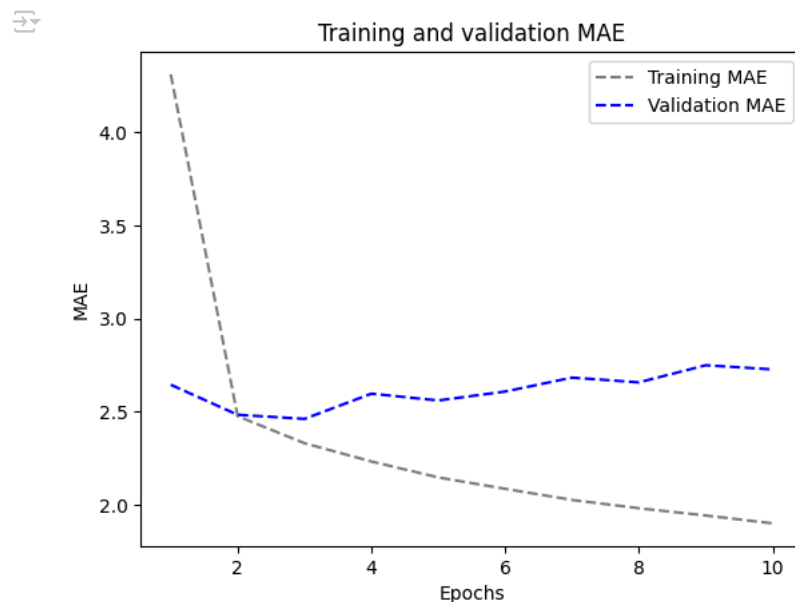
```

import matplotlib.pyplot as plt

loss = history.history["mae"]
val_loss = history.history["val_mae"]

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

```



#### ✓ 4)32-unit LSTM stacked configuration

```

inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(32, return_sequences=True)(inputs)
x = layers.LSTM(32)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked2.keras",

```

```

save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)
model = keras.models.load_model("jena_LSTM_stacked2.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")

```

```

Epoch 1/10
819/819 [=====] - 222s 266ms/step - loss: 21.8000 - mae: 3.3354 - val_loss: 11.3831 - val_mae: 2.6227
Epoch 2/10
819/819 [=====] - 260s 317ms/step - loss: 8.6256 - mae: 2.2852 - val_loss: 10.9907 - val_mae: 2.6210
Epoch 3/10
819/819 [=====] - 218s 266ms/step - loss: 7.3192 - mae: 2.1068 - val_loss: 10.6014 - val_mae: 2.5613
Epoch 4/10
819/819 [=====] - 211s 258ms/step - loss: 6.3496 - mae: 1.9587 - val_loss: 11.5484 - val_mae: 2.6723
Epoch 5/10
819/819 [=====] - 211s 257ms/step - loss: 5.5186 - mae: 1.8213 - val_loss: 11.7567 - val_mae: 2.7149
Epoch 6/10
819/819 [=====] - 211s 257ms/step - loss: 4.8414 - mae: 1.6998 - val_loss: 11.7850 - val_mae: 2.6971
Epoch 7/10
819/819 [=====] - 216s 263ms/step - loss: 4.3529 - mae: 1.6088 - val_loss: 12.6021 - val_mae: 2.7976
Epoch 8/10
819/819 [=====] - 213s 259ms/step - loss: 4.0156 - mae: 1.5416 - val_loss: 13.0680 - val_mae: 2.8346
Epoch 9/10
819/819 [=====] - 253s 309ms/step - loss: 3.7335 - mae: 1.4831 - val_loss: 13.3894 - val_mae: 2.8597
Epoch 10/10
819/819 [=====] - 215s 263ms/step - loss: 3.4744 - mae: 1.4282 - val_loss: 13.2002 - val_mae: 2.8284
405/405 [=====] - 42s 101ms/step - loss: 11.5409 - mae: 2.6758
Test MAE: 2.68

```

```

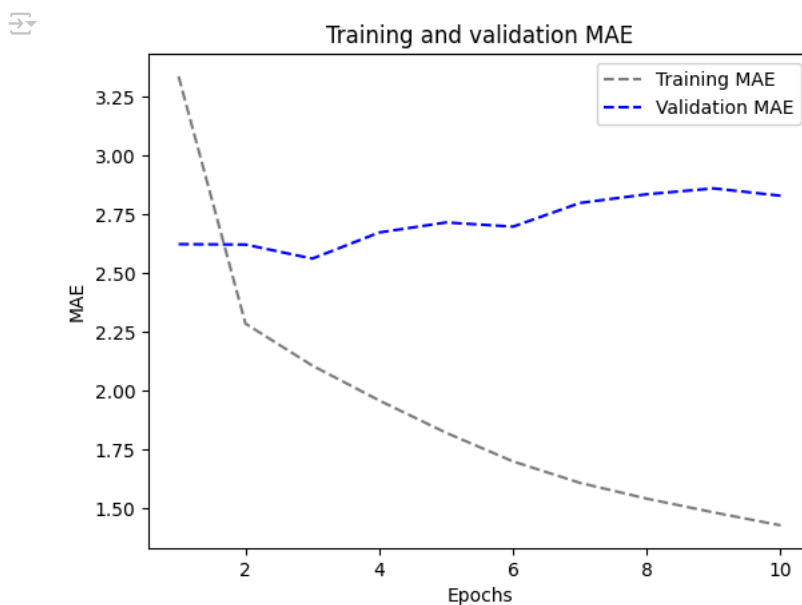
import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]

```

```

epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs, val_loss, 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: Eight units in a stacked configuration

```

inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(8, return_sequences=True)(inputs)
x = layers.LSTM(8)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

```

```

callbacks = [
    keras.callbacks.ModelCheckpoint("jena_LSTM_stacked3.keras",
                                    save_best_only=True)
]
model.compile(optimizer="rmsprop", loss="mse", metrics=["mae"])
history = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)
model = keras.models.load_model("jena_LSTM_stacked3.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")

```

```

Epoch 1/10
819/819 [=====] - 149s 175ms/step - loss: 62.8721 - mae: 6.0103 - val_loss: 29.8286 - val_mae: 4.0509
Epoch 2/10
819/819 [=====] - 122s 149ms/step - loss: 18.6538 - mae: 3.2166 - val_loss: 12.3282 - val_mae: 2.6659
Epoch 3/10
819/819 [=====] - 122s 148ms/step - loss: 10.9183 - mae: 2.5651 - val_loss: 9.9808 - val_mae: 2.4532
Epoch 4/10
819/819 [=====] - 137s 167ms/step - loss: 9.8589 - mae: 2.4430 - val_loss: 9.8092 - val_mae: 2.4327
Epoch 5/10
819/819 [=====] - 120s 146ms/step - loss: 9.4959 - mae: 2.3952 - val_loss: 9.8979 - val_mae: 2.4579
Epoch 6/10
819/819 [=====] - 121s 147ms/step - loss: 9.2992 - mae: 2.3688 - val_loss: 10.1846 - val_mae: 2.5007
Epoch 7/10
819/819 [=====] - 119s 145ms/step - loss: 9.1286 - mae: 2.3491 - val_loss: 9.9757 - val_mae: 2.4679
Epoch 8/10
819/819 [=====] - 122s 148ms/step - loss: 9.0125 - mae: 2.3346 - val_loss: 10.1919 - val_mae: 2.4977
Epoch 9/10
819/819 [=====] - 119s 145ms/step - loss: 8.8927 - mae: 2.3206 - val_loss: 9.9422 - val_mae: 2.4606
Epoch 10/10
819/819 [=====] - 120s 146ms/step - loss: 8.7885 - mae: 2.3090 - val_loss: 9.8017 - val_mae: 2.4570
405/405 [=====] - 25s 60ms/step - loss: 10.4392 - mae: 2.5426
Test MAE: 2.54

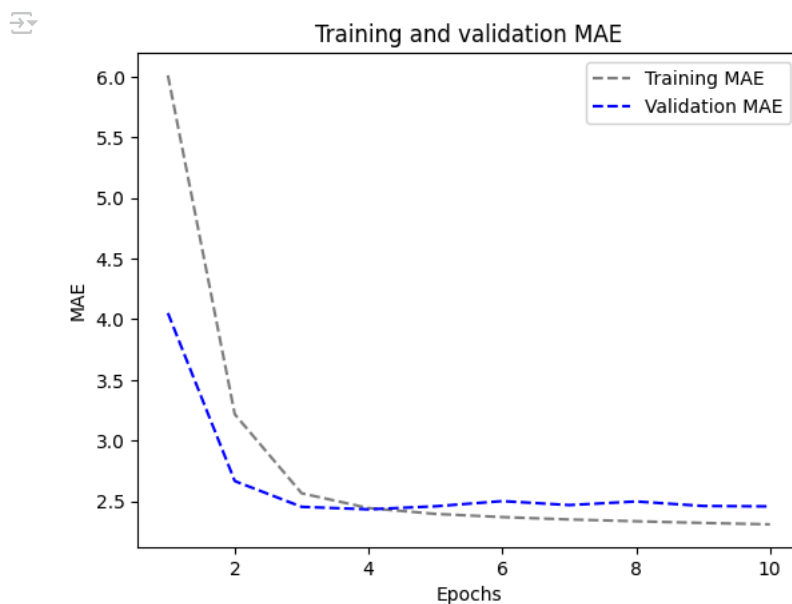
```

```

import matplotlib.pyplot as plt
loss = history.history["mae"]
val_loss = history.history["val_mae"]

epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs, val_loss, 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, dropout-regularized model

```

inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.LSTM(8, recurrent_dropout=0.5, return_sequences=True)(inputs)

```

```

x = layers.LSTM(8, recurrent_dropout=0.5)(x)
x = layers.Dropout(0.5)(x)
outputs = layers.Dense(1)(x)
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(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)
model = keras.models.load_model("jena_stacked_LSTM_dropout.keras")
print(f"Test MAE: {model.evaluate(test_dataset)[1]:.2f}")

```

```

Epoch 1/10
819/819 [=====] - 233s 278ms/step - loss: 80.6144 - mae: 6.9262 - val_loss: 39.6168 - val_mae: 4.6831
Epoch 2/10
819/819 [=====] - 226s 276ms/step - loss: 33.6996 - mae: 4.3223 - val_loss: 15.1408 - val_mae: 2.9103
Epoch 3/10
819/819 [=====] - 224s 273ms/step - loss: 24.7884 - mae: 3.7610 - val_loss: 11.3518 - val_mae: 2.5805
Epoch 4/10
819/819 [=====] - 222s 271ms/step - loss: 22.7452 - mae: 3.6127 - val_loss: 10.6543 - val_mae: 2.5217
Epoch 5/10
819/819 [=====] - 222s 271ms/step - loss: 21.3253 - mae: 3.5019 - val_loss: 10.3918 - val_mae: 2.4992
Epoch 6/10
819/819 [=====] - 223s 272ms/step - loss: 20.4405 - mae: 3.4336 - val_loss: 9.8008 - val_mae: 2.4340
Epoch 7/10
819/819 [=====] - 223s 272ms/step - loss: 19.4473 - mae: 3.3523 - val_loss: 10.9866 - val_mae: 2.5522
Epoch 8/10
819/819 [=====] - 226s 276ms/step - loss: 18.7463 - mae: 3.2958 - val_loss: 10.3414 - val_mae: 2.4933
Epoch 9/10
819/819 [=====] - 223s 271ms/step - loss: 18.2033 - mae: 3.2514 - val_loss: 10.1614 - val_mae: 2.4780
Epoch 10/10
819/819 [=====] - 224s 273ms/step - loss: 17.6642 - mae: 3.2091 - val_loss: 9.6813 - val_mae: 2.4176
405/405 [=====] - 27s 64ms/step - loss: 11.4865 - mae: 2.6063
Test MAE: 2.61

```

```
import matplotlib.pyplot as plt
```

```

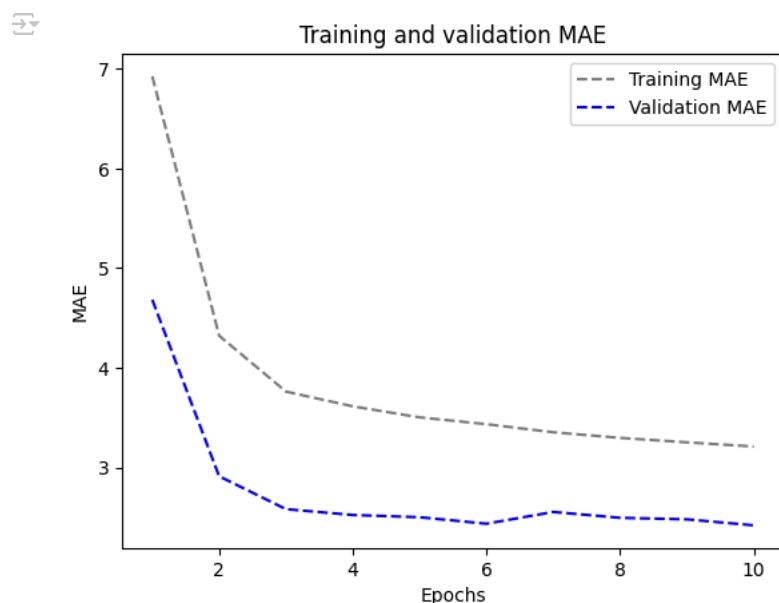
loss = history.history["mae"]
val_loss = history.history["val_mae"]

```

```

epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, color="grey", linestyle="dashed", label="Training MAE")
plt.plot(epochs, val_loss, 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 model

```
inputs = keras.Input(shape=(sequence_length, raw_data.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 = model.fit(train_dataset,
                    epochs=10,
                    validation_data=val_dataset,
                    callbacks=callbacks)

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

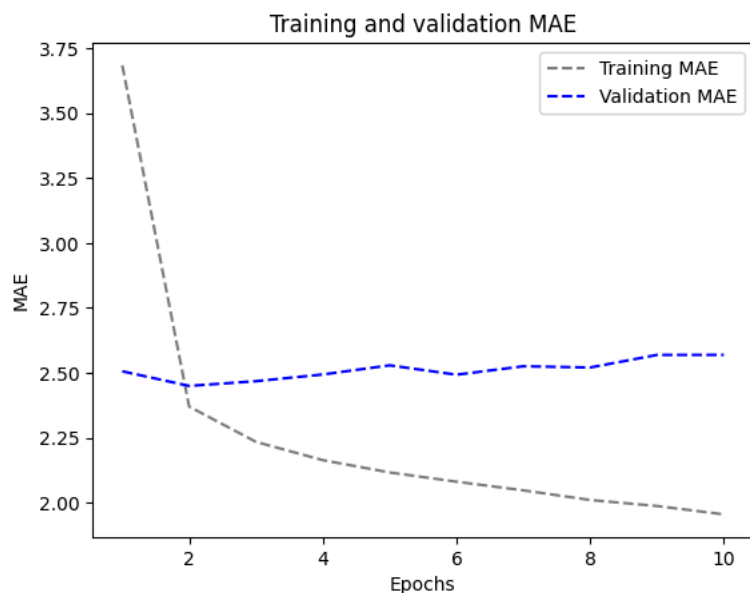
```
Epoch 1/10
819/819 [=====] - 145s 170ms/step - loss: 26.3385 - mae: 3.6835 - val_loss: 10.5120 - val_mae: 2.5064
Epoch 2/10
819/819 [=====] - 150s 183ms/step - loss: 9.2395 - mae: 2.3707 - val_loss: 10.1170 - val_mae: 2.4501
Epoch 3/10
819/819 [=====] - 137s 167ms/step - loss: 8.2708 - mae: 2.2348 - val_loss: 10.2597 - val_mae: 2.4683
Epoch 4/10
819/819 [=====] - 137s 167ms/step - loss: 7.7490 - mae: 2.1645 - val_loss: 10.3628 - val_mae: 2.4941
Epoch 5/10
819/819 [=====] - 135s 165ms/step - loss: 7.3933 - mae: 2.1171 - val_loss: 10.6053 - val_mae: 2.5292
Epoch 6/10
819/819 [=====] - 134s 163ms/step - loss: 7.1202 - mae: 2.0816 - val_loss: 10.2853 - val_mae: 2.4932
Epoch 7/10
819/819 [=====] - 134s 164ms/step - loss: 6.8830 - mae: 2.0482 - val_loss: 10.5008 - val_mae: 2.5256
Epoch 8/10
819/819 [=====] - 136s 166ms/step - loss: 6.6300 - mae: 2.0112 - val_loss: 10.4050 - val_mae: 2.5209
Epoch 9/10
819/819 [=====] - 150s 183ms/step - loss: 6.4856 - mae: 1.9880 - val_loss: 10.8708 - val_mae: 2.5693
Epoch 10/10
819/819 [=====] - 135s 164ms/step - loss: 6.2739 - mae: 1.9558 - val_loss: 10.8510 - val_mae: 2.5694
405/405 [=====] - 28s 66ms/step - loss: 11.1630 - mae: 2.6156
Test MAE: 2.62
```

```
import matplotlib.pyplot as plt

loss = history.history["mae"]
val_loss = history.history["val_mae"]

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





## ✓ combining 1D Convolutional Networks (Conv1D) with LSTM layers

```
inputs = keras.Input(shape=(sequence_length, raw_data.shape[-1]))
x = layers.Conv1D(64, 3, activation='relu')(inputs)
x = layers.MaxPooling1D(3)(x)
x = layers.Conv1D(128, 3, activation='relu')(x)
x = layers.GlobalMaxPooling1D()(x)
x = layers.Reshape((-1, 128))(x) # Reshape the data to be 3D
x = layers.LSTM(16)(x)
outputs = layers.Dense(1)(x)
model = keras.Model(inputs, outputs)

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

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

history = model.fit(train_dataset, epochs=10, validation_data=val_dataset, callbacks=callbacks)

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



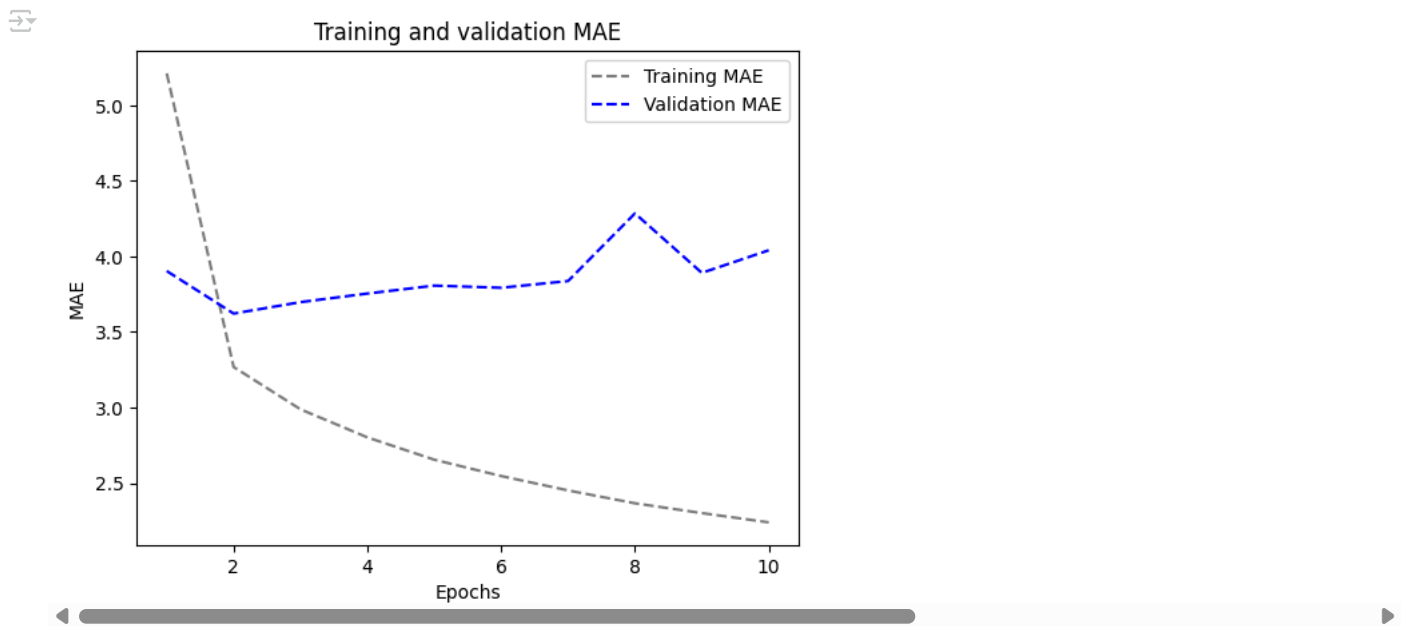
```
Epoch 1/10
819/819 [=====] - 106s 124ms/step - loss: 48.5553 - mae: 5.2119 - val_loss: 25.3878 - val_mae: 3.9035
Epoch 2/10
819/819 [=====] - 99s 120ms/step - loss: 17.8188 - mae: 3.2683 - val_loss: 21.0572 - val_mae: 3.6218
Epoch 3/10
819/819 [=====] - 98s 119ms/step - loss: 14.7705 - mae: 2.9880 - val_loss: 22.1986 - val_mae: 3.6977
Epoch 4/10
819/819 [=====] - 99s 120ms/step - loss: 13.0422 - mae: 2.8023 - val_loss: 22.9818 - val_mae: 3.7545
Epoch 5/10
819/819 [=====] - 100s 121ms/step - loss: 11.7727 - mae: 2.6547 - val_loss: 22.9659 - val_mae: 3.8071
Epoch 6/10
819/819 [=====] - 100s 122ms/step - loss: 10.8887 - mae: 2.5465 - val_loss: 23.2072 - val_mae: 3.7926
Epoch 7/10
819/819 [=====] - 98s 119ms/step - loss: 10.1294 - mae: 2.4513 - val_loss: 23.0342 - val_mae: 3.8373
Epoch 8/10
819/819 [=====] - 100s 122ms/step - loss: 9.4733 - mae: 2.3661 - val_loss: 28.1948 - val_mae: 4.2850
Epoch 9/10
819/819 [=====] - 99s 120ms/step - loss: 8.9798 - mae: 2.3012 - val_loss: 23.5628 - val_mae: 3.8912
Epoch 10/10
819/819 [=====] - 97s 118ms/step - loss: 8.5445 - mae: 2.2399 - val_loss: 25.2865 - val_mae: 4.0408
405/405 [=====] - 20s 47ms/step - loss: 23.8323 - mae: 3.8721
Test MAE: 3.87
```

```
import matplotlib.pyplot as plt

loss = history.history["mae"]
val_loss = history.history["val_mae"]

epochs = range(1, len(loss) + 1)
plt.figure()
plt.plot(epochs, loss, color="grey", linestyle="dashed", label="Training MAE")
```

```
plt.plot(epochs, val_loss, color="blue", linestyle="dashed", label="Validation MAE")
plt.title("Training and validation MAE")
plt.xlabel("Epochs")
plt.ylabel("MAE")
plt.legend()
plt.show()
```



```
import matplotlib.pyplot as plt

Models = ("1", "2", "3", "4", "5", "6", "7", "8", "9", "10", "11", "12", "13", "14")
Mae = (2.62, 2.67, 3.2, 9.92, 9.9, 2.5, 2.59, 2.54, 2.58, 2.68, 2.55, 2.56, 2.59, 4.01)

# 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()
```

