Time Series Prediction

In [108]:

```
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.utils import shuffle
from keras.models import Sequential
from keras.layers import Dense, Flatten, InputLayer, LSTM, Dropout, BatchNormalization,
Conv1D, MaxPooling1D
from keras.callbacks import EarlyStopping
import json
import random
from keras import backend as K
```

Read in Data

In [109]:

```
# Read in feature data
with open('../../../../data/feature_database.json') as json_database:
    database = json.load(json_database)
# Concat data
feature_data = None
for i in database:
    # Filter emission data
    if (database[i]['sector'] != 'target_values' and
        database[i]['sector'] != 'greenhouse_emissions'):
        new_data = pd.read_json(database[i]['data'])
        if feature_data is None:
            feature_data = new_data
        else:
            feature_data = pd.concat([feature_data, new_data], axis=1, join="inner")
    else:
        print(f"Feature not used: {i}")
feature_data = feature_data.values
feature_data = feature_data.astype('float64')
print(f"Shape input features: {feature_data.shape}")
#feature_data.head()
```

```
Feature not used: E_Mio.tonnes_CO2
Feature not used: M_Mio.tonnes_CO2
Feature not used: ECO_Mio.tonnes_CO2
Feature not used: Total_CO2_Emission
Shape input features: (111, 40)
```

In [110]:

```
# Read in emission data
emission_data = pd.read_csv('../../../../data/greenhouse_emissions/oeko-institut_sektorale_abgrenzung_treibhausgasemissionen_daten_sektor_monthly.csv')
emission_data = emission_data['Total_CO2_Emission'].values
emission_data = emission_data.astype('float64')
# Take only the emissions on which we have indicators
emission_data = emission_data[len(emission_data)-feature_data.shape[0]:]
print(f"Shape output data: {emission_data.shape}")
```

```
Shape output data: (111,)
```

In [111]:

```
# Convert an array of values into a dataset matrix
def sliding_window(input, output, look_back=1, horizon=1, shuffle=False):
    dataX, dataY = [], []
    if len(input) != len(output):
        raise ValueError('Input and ouput do not have same length!')
    for i in range(len(input)-look_back-horizon):
        dataX.append(input[i:(i+look_back)])
        dataY.append(output[(i+look_back):(i+look_back+horizon)])
    # Shuffle windows
    if shuffle is True:
        dataX, dataY = shuffle(dataX, dataY, random_state=0)
    return np.array(dataX), np.array(dataY)
```

In [112]:

```
def r2_keras(y_true, y_pred):
    SS_res =  K.sum(K.square(y_true - y_pred))
    SS_tot = K.sum(K.square(y_true - K.mean(y_true)))
    return ( 1 - SS_res/(SS_tot + K.epsilon()) )
```

In [113]:

```
def plot_model_history(history, ax=None, metric='loss', ep_start=1, ep_stop=None, monitor='val_loss', mode='min', plttitle=None):
    if ax is None:
        fig,ax = plt.subplots()
    if ep_stop is None:
        ep_stop = len(history.epoch)
    if plttitle is None:
        plttitle = metric[0].swapcase() + metric[1:] + ' During Training'
    ax.plot(np.arange(ep_start,ep_stop+1, dtype='int'),history.history[metric][ep_start-1:ep_stop])
    ax.plot(np.arange(ep_start,ep_stop+1, dtype='int'),history.history['val_' + metric][ep_start-1:ep_stop])
    ax.set(title=plttitle)
    ax.set(ylabel=metric[0].swapcase() + metric[1:])
    ax.set(xlabel='Epoch')
    ax.legend(['train', 'val'], loc='upper right')
```

In [114]:

```
scaler = StandardScaler()
#scaler = MinMaxScaler()
feature_data = scaler.fit_transform(feature_data)

look_back = 12  # months
horizon = 6     # months
split_ratio = 0.75
shuffle = True

# Split into train and test sets
train_size = int(len(feature_data) * split_ratio)
test_size = len(feature_data) - train_size
if test_size < (look_back+horizon):
    raise ValueError('Split ratio too small. Increase test size!')
```

Long Short-Term Memory

In [115]:

```
def train_lstm(trainX, trainY, testX,  testY, lock_back, horizon):
    es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=100, restore
_best_weights=True)

    model = Sequential(name='LSTM')
    model.add(InputLayer(input_shape=(look_back, trainX.shape[2])))
    model.add(LSTM(256, return_sequences=True, name="LSTM_1"))
    model.add(BatchNormalization())
    model.add(LSTM(128, return_sequences=True, name="LSTM_2"))
    model.add(BatchNormalization())
    #model.add(LSTM(96, return_sequences=True, name="LSTM_3"))
    #model.add(BatchNormalization())
    model.add(LSTM(64, return_sequences=False, name="LSTM_4"))
    model.add(BatchNormalization())
    model.add(Dense(64, activation='relu', name="LSTM_Dense1"))
    #model.add(Dropout(0.2))
    model.add(Dense(32, activation='relu', name="LSTM_Dense2"))
    #model.add(Dropout(0.2))
    model.add(Dense(16, activation='relu', name="LSTM_Dense3"))
    model.add(Dense(horizon,activation="linear",name="LSTM_output"))

    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[r2_keras])
    model.summary()
    history = model.fit(trainX, trainY, validation_split=0.2, epochs=250, batch_size=8,
verbose=1, callbacks=[es])
    # Estimate model performance
    trainScore = model.evaluate(trainX, trainY, verbose=1)
    print('Train Score: %.2f MSE (%.2f RMSE)' % (trainScore[0], math.sqrt(trainScore[0
])))
    testScore = model.evaluate(testX, testY, verbose=1)
    print('Test Score: %.2f MSE (%.2f RMSE)' % (testScore[0], math.sqrt(testScore[0])))

    # Generate predictions for training
    trainPredict = model.predict(trainX)
    testPredict = model.predict(testX)

    return model, trainPredict, testPredict
```

Convolutional Neural Network

In [116]:

```
def train_cnn(trainX, trainY, testX,  testY, lock_back, horizon):
    es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=25, restore_
best_weights=True)

    model = Sequential(name='CNN')
    model.add(InputLayer(input_shape=(look_back, trainX.shape[2])))
    model.add(Conv1D(filters=128, kernel_size=5, activation='elu', name="Conv_1"))
    #model.add(MaxPooling1D(pool_size=2, name='MaxPool_1'))
    model.add(BatchNormalization())
    model.add(Conv1D(filters=64, kernel_size=3, activation='elu', name="Conv_2"))
    #model.add(MaxPooling1D(pool_size=2, name='MaxPool_2'))
    model.add(BatchNormalization())
    model.add(Conv1D(filters=32, kernel_size=2, activation='relu', name="Conv_3"))
    #model.add(MaxPooling1D(pool_size=2, name='MaxPool_3'))
    model.add(BatchNormalization())
    model.add(Flatten())
    #model.add(Dropout(0.2))
    model.add(Dense(16, activation='elu', name='Dense_1'))
    #model.add(Dense(8, activation='elu', name='Dense_2'))
    model.add(Dense(horizon, activation='linear', name="CNN_output"))

    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[r2_keras])
    model.summary()
    model.fit(trainX, trainY, validation_split=0.2, epochs=250, batch_size=8, verbose=1
, callbacks=[es])
    # Estimate model performance
    trainScore = model.evaluate(trainX, trainY, verbose=0)
    print('Train Score: %.2f MSE (%.2f RMSE)' % (trainScore[0], math.sqrt(trainScore[0
])))
    testScore = model.evaluate(testX, testY, verbose=0)
    print('Test Score: %.2f MSE (%.2f RMSE)' % (testScore[0], math.sqrt(testScore[0])))

    # Generate predictions for training
    trainPredict = model.predict(trainX)
    testPredict = model.predict(testX)

    return model, trainPredict, testPredict
```

In [117]:

```
from keras.models import Model
from keras.layers import Input, Conv1D, Dense, Activation, Dropout, Lambda, Multiply, A
dd, Concatenate, GlobalMaxPooling1D
from keras.optimizers import Adam
from keras.layers import Dense, Flatten, InputLayer, LSTM, Dropout, BatchNormalization,
Conv1D, MaxPooling1D


def train_wavenet(trainX, trainY, testX,  testY, lock_back, horizon):
    es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=500, restore
_best_weights=True)

    # convolutional operation parameters
    n_filters = 32 # 32
    filter_width = 2
    dilation_rates = [2**i for i in range(4)] * 2

    # define an input history series and pass it through a stack of dilated causal conv
olution blocks.
    history_seq = Input(shape=(look_back, trainX.shape[2]))
    x = history_seq

    skips = []
    for dilation_rate in dilation_rates:

        # preprocessing - equivalent to time-distributed dense
        x = Conv1D(16, 1, padding='same', activation='relu')(x)

        # filter convolution
        x_f = Conv1D(filters=n_filters,
                     kernel_size=filter_width,
                     padding='causal',
                     dilation_rate=dilation_rate)(x)

        # gating convolution
        x_g = Conv1D(filters=n_filters,
                     kernel_size=filter_width,
                     padding='causal',
                     dilation_rate=dilation_rate)(x)

        # multiply filter and gating branches
        z = Multiply()([Activation('tanh')(x_f),
                        Activation('sigmoid')(x_g)])

        # postprocessing - equivalent to time-distributed dense
        z = Conv1D(16, 1, padding='same', activation='relu')(z)

        # residual connection
        x = Add()([x, z])

        # collect skip connections
        skips.append(z)

    # add all skip connection outputs
    out = Activation('relu')(Add()(skips))

    # final time-distributed dense layers
    out = Conv1D(128, 1, padding='same')(out)
    out = Activation('relu')(out)
```

```
    #out = Dropout(.2)(out)
    #out = Conv1D(1, 1, padding='same')(out)
    out = GlobalMaxPooling1D()(out)
    out = Dense(horizon, activation='linear', name="final_dense_layer")(out)

    model = Model(history_seq, out)
    model.compile(loss='mean_squared_error', optimizer='adam', metrics=[r2_keras])
    model.summary()
    history = model.fit(trainX, trainY, validation_split=0.2, epochs=250, batch_size=8,
verbose=1, callbacks=[es])
    # Estimate model performance
    trainScore = model.evaluate(trainX, trainY, verbose=0)
    print('Train Score: %.2f MSE (%.2f RMSE)' % (trainScore[0], math.sqrt(trainScore[0
]))))
    testScore = model.evaluate(testX, testY, verbose=0)
    print('Test Score: %.2f MSE (%.2f RMSE)' % (testScore[0], math.sqrt(testScore[0])))

    # Generate predictions for training
    trainPredict = model.predict(trainX)
    testPredict = model.predict(testX)

    return model, trainPredict, testPredict, history
```

In [118]:

```
# Features as input
trainX, trainY = sliding_window(feature_data[0:train_size,:],
                                emission_data[0:train_size],
                                look_back,
                                horizon)
testX, testY = sliding_window(feature_data[train_size:len(feature_data),:],
                              emission_data[train_size:len(emission_data)],
                              look_back,
                              horizon)
```

In [119]:

```
print("Shape of data:")
print(trainX.shape)
print(trainY.shape)
print(testX.shape)
print(testY.shape)
```

```
Shape of data:
(65, 12, 40)
(65, 6)
(10, 12, 40)
(10, 6)
```

Train Model

In [120]:

```
#Varying number of features

num_of_feats = 15
random_list = []

for i in range(num_of_feats):
        value = random.randint(0, 39)

        while value in random_list:
            value = random.randint(0, 39)

        random_list.append(value)

random_list
```

Out[120]:

```
[9, 24, 21, 13, 3, 19, 32, 25, 7, 16, 14, 0, 26, 35, 8]
```

In [121]:

```
trainX = trainX[:, :, random_list]
print(trainX.shape)
testX = testX[:, :, random_list]
print(testX.shape)
```

```
(65, 12, 15)
(10, 12, 15)
```

In [122]:

```
# Create and fit Multilayer Perceptron model for every indicator
trainPredictPlot = np.empty_like(emission_data)
trainPredictPlot[:] = np.nan
testPredictPlot = np.empty_like(emission_data)
testPredictPlot[:] = np.nan



# Train model and generate predictions
model, trainPredict, testPredict, history = train_wavenet(trainX, trainY, testX, testY,
                                                look_back, horizon)

# Shift train predictions for plotting
for t in range(len(trainPredict)):
    trainPredictPlot[t+look_back:t+look_back+horizon] = trainPredict[t, :]
for t in range(len(testPredict)):
    testPredictPlot[len(trainPredict)+t+look_back+horizon:len(trainPredict)+
                    t+look_back+(horizon*2)] = testPredict[t, :]
```

```
Model: "model_7"
__________________________________________________________________________________________
Layer (type)                 Output Shape              Param #     Connected
to
==========================================================================================
input_7 (InputLayer)         (None, 12, 15)            0
__________________________________________________________________________________________
conv1d_263 (Conv1D)          (None, 12, 16)            256         input_7
[0][0]
__________________________________________________________________________________________
conv1d_264 (Conv1D)          (None, 12, 32)            1056        conv1d_26
3[0][0]
__________________________________________________________________________________________
conv1d_265 (Conv1D)          (None, 12, 32)            1056        conv1d_26
3[0][0]
__________________________________________________________________________________________
activation_141 (Activation)  (None, 12, 32)            0           conv1d_26
4[0][0]
__________________________________________________________________________________________
activation_142 (Activation)  (None, 12, 32)            0           conv1d_26
5[0][0]
__________________________________________________________________________________________
multiply_65 (Multiply)       (None, 12, 32)            0           activatio
n_141[0][0]
                                                                   activatio
n_142[0][0]
__________________________________________________________________________________________
conv1d_266 (Conv1D)          (None, 12, 16)            528         multiply_
65[0][0]
__________________________________________________________________________________________
add_71 (Add)                 (None, 12, 16)            0           conv1d_26
3[0][0]
                                                                   conv1d_26
6[0][0]
__________________________________________________________________________________________
conv1d_267 (Conv1D)          (None, 12, 16)            272         add_71[0]
[0]
__________________________________________________________________________________________
conv1d_268 (Conv1D)          (None, 12, 32)            1056        conv1d_26
7[0][0]
__________________________________________________________________________________________
conv1d_269 (Conv1D)          (None, 12, 32)            1056        conv1d_26
7[0][0]
__________________________________________________________________________________________
activation_143 (Activation)  (None, 12, 32)            0           conv1d_26
8[0][0]
__________________________________________________________________________________________
```

```
__________________________
activation_144 (Activation)     (None, 12, 32)       0           conv1d_26
9[0][0]
__________________________________________________________________________
__________________________
multiply_66 (Multiply)          (None, 12, 32)       0           activatio
n_143[0][0]
                                                                 activatio
n_144[0][0]
__________________________________________________________________________
__________________________
conv1d_270 (Conv1D)             (None, 12, 16)       528         multiply_
66[0][0]
__________________________________________________________________________
__________________________
add_72 (Add)                    (None, 12, 16)       0           conv1d_26
7[0][0]
                                                                 conv1d_27
0[0][0]
__________________________________________________________________________
__________________________
conv1d_271 (Conv1D)             (None, 12, 16)       272         add_72[0]
[0]
__________________________________________________________________________
__________________________
conv1d_272 (Conv1D)             (None, 12, 32)       1056        conv1d_27
1[0][0]
__________________________________________________________________________
__________________________
conv1d_273 (Conv1D)             (None, 12, 32)       1056        conv1d_27
1[0][0]
__________________________________________________________________________
__________________________
activation_145 (Activation)     (None, 12, 32)       0           conv1d_27
2[0][0]
__________________________________________________________________________
__________________________
activation_146 (Activation)     (None, 12, 32)       0           conv1d_27
3[0][0]
__________________________________________________________________________
__________________________
multiply_67 (Multiply)          (None, 12, 32)       0           activatio
n_145[0][0]
                                                                 activatio
n_146[0][0]
__________________________________________________________________________
__________________________
conv1d_274 (Conv1D)             (None, 12, 16)       528         multiply_
67[0][0]
__________________________________________________________________________
__________________________
add_73 (Add)                    (None, 12, 16)       0           conv1d_27
1[0][0]
                                                                 conv1d_27
4[0][0]
__________________________________________________________________________
__________________________
conv1d_275 (Conv1D)             (None, 12, 16)       272         add_73[0]
[0]
__________________________________________________________________________
__________________________
```

```
conv1d_276 (Conv1D)             (None, 12, 32)       1056        conv1d_27
5[0][0]
__________________________________________________________________________
_____________________
conv1d_277 (Conv1D)             (None, 12, 32)       1056        conv1d_27
5[0][0]
__________________________________________________________________________
_____________________
activation_147 (Activation)     (None, 12, 32)       0           conv1d_27
6[0][0]
__________________________________________________________________________
_____________________
activation_148 (Activation)     (None, 12, 32)       0           conv1d_27
7[0][0]
__________________________________________________________________________
_____________________
multiply_68 (Multiply)          (None, 12, 32)       0           activatio
n_147[0][0]
                                                                 activatio
n_148[0][0]
__________________________________________________________________________
_____________________
conv1d_278 (Conv1D)             (None, 12, 16)       528         multiply_
68[0][0]
__________________________________________________________________________
_____________________
add_74 (Add)                    (None, 12, 16)       0           conv1d_27
5[0][0]
                                                                 conv1d_27
8[0][0]
__________________________________________________________________________
_____________________
conv1d_279 (Conv1D)             (None, 12, 16)       272         add_74[0]
[0]
__________________________________________________________________________
_____________________
conv1d_280 (Conv1D)             (None, 12, 32)       1056        conv1d_27
9[0][0]
__________________________________________________________________________
_____________________
conv1d_281 (Conv1D)             (None, 12, 32)       1056        conv1d_27
9[0][0]
__________________________________________________________________________
_____________________
activation_149 (Activation)     (None, 12, 32)       0           conv1d_28
0[0][0]
__________________________________________________________________________
_____________________
activation_150 (Activation)     (None, 12, 32)       0           conv1d_28
1[0][0]
__________________________________________________________________________
_____________________
multiply_69 (Multiply)          (None, 12, 32)       0           activatio
n_149[0][0]
                                                                 activatio
n_150[0][0]
__________________________________________________________________________
_____________________
conv1d_282 (Conv1D)             (None, 12, 16)       528         multiply_
69[0][0]
__________________________________________________________________________
```

```
__________________________
add_75 (Add)                 (None, 12, 16)       0           conv1d_27
9[0][0]
                                                             conv1d_28
2[0][0]
__________________________________________________________________________
__________________________
conv1d_283 (Conv1D)          (None, 12, 16)       272         add_75[0]
[0]
__________________________________________________________________________
__________________________
conv1d_284 (Conv1D)          (None, 12, 32)       1056        conv1d_28
3[0][0]
__________________________________________________________________________
__________________________
conv1d_285 (Conv1D)          (None, 12, 32)       1056        conv1d_28
3[0][0]
__________________________________________________________________________
__________________________
activation_151 (Activation)  (None, 12, 32)       0           conv1d_28
4[0][0]
__________________________________________________________________________
__________________________
activation_152 (Activation)  (None, 12, 32)       0           conv1d_28
5[0][0]
__________________________________________________________________________
__________________________
multiply_70 (Multiply)       (None, 12, 32)       0           activatio
n_151[0][0]
                                                             activatio
n_152[0][0]
__________________________________________________________________________
__________________________
conv1d_286 (Conv1D)          (None, 12, 16)       528         multiply_
70[0][0]
__________________________________________________________________________
__________________________
add_76 (Add)                 (None, 12, 16)       0           conv1d_28
3[0][0]
                                                             conv1d_28
6[0][0]
__________________________________________________________________________
__________________________
conv1d_287 (Conv1D)          (None, 12, 16)       272         add_76[0]
[0]
__________________________________________________________________________
__________________________
conv1d_288 (Conv1D)          (None, 12, 32)       1056        conv1d_28
7[0][0]
__________________________________________________________________________
__________________________
conv1d_289 (Conv1D)          (None, 12, 32)       1056        conv1d_28
7[0][0]
__________________________________________________________________________
__________________________
activation_153 (Activation)  (None, 12, 32)       0           conv1d_28
8[0][0]
__________________________________________________________________________
__________________________
activation_154 (Activation)  (None, 12, 32)       0           conv1d_28
9[0][0]
```

```
__________________________________________________________________________________________________
_____________________________
multiply_71 (Multiply)          (None, 12, 32)       0           activatio
n_153[0][0]
                                                                 activatio
n_154[0][0]
__________________________________________________________________________________________________
_____________________________
conv1d_290 (Conv1D)             (None, 12, 16)       528         multiply_
71[0][0]
__________________________________________________________________________________________________
_____________________________
add_77 (Add)                    (None, 12, 16)       0           conv1d_28
7[0][0]
                                                                 conv1d_29
0[0][0]
__________________________________________________________________________________________________
_____________________________
conv1d_291 (Conv1D)             (None, 12, 16)       272         add_77[0]
[0]
__________________________________________________________________________________________________
_____________________________
conv1d_292 (Conv1D)             (None, 12, 32)       1056        conv1d_29
1[0][0]
__________________________________________________________________________________________________
_____________________________
conv1d_293 (Conv1D)             (None, 12, 32)       1056        conv1d_29
1[0][0]
__________________________________________________________________________________________________
_____________________________
activation_155 (Activation)     (None, 12, 32)       0           conv1d_29
2[0][0]
__________________________________________________________________________________________________
_____________________________
activation_156 (Activation)     (None, 12, 32)       0           conv1d_29
3[0][0]
__________________________________________________________________________________________________
_____________________________
multiply_72 (Multiply)          (None, 12, 32)       0           activatio
n_155[0][0]
                                                                 activatio
n_156[0][0]
__________________________________________________________________________________________________
_____________________________
conv1d_294 (Conv1D)             (None, 12, 16)       528         multiply_
72[0][0]
__________________________________________________________________________________________________
_____________________________
add_79 (Add)                    (None, 12, 16)       0           conv1d_26
6[0][0]
                                                                 conv1d_27
0[0][0]
                                                                 conv1d_27
4[0][0]
                                                                 conv1d_27
8[0][0]
                                                                 conv1d_28
2[0][0]
                                                                 conv1d_28
6[0][0]
                                                                 conv1d_29
```

```
0[0][0]
                                                                 conv1d_29
4[0][0]
__________________________________________________________________________
_____________________
activation_157 (Activation)     (None, 12, 16)       0           add_79[0]
[0]
__________________________________________________________________________
_____________________
conv1d_295 (Conv1D)             (None, 12, 128)      2176        activatio
n_157[0][0]
__________________________________________________________________________
_____________________
activation_158 (Activation)     (None, 12, 128)      0           conv1d_29
5[0][0]
__________________________________________________________________________
_____________________
global_max_pooling1d_7 (GlobalM (None, 128)          0           activatio
n_158[0][0]
__________________________________________________________________________
_____________________
final_dense_layer (Dense)       (None, 6)            774         global_ma
x_pooling1d_7[0][0]
==========================================================================
========================
Total params: 26,230
Trainable params: 26,230
Non-trainable params: 0
__________________________________________________________________________
_____________________
Train on 52 samples, validate on 13 samples
Epoch 1/250
52/52 [==============================] - 1s 27ms/step - loss: 4822.9122 -
r2_keras: -191.9679 - val_loss: 4596.8838 - val_r2_keras: -238.1821
Epoch 2/250
52/52 [==============================] - 0s 2ms/step - loss: 4706.6752 - r
2_keras: -178.7391 - val_loss: 4445.9091 - val_r2_keras: -230.4048
Epoch 3/250
52/52 [==============================] - 0s 2ms/step - loss: 4435.3779 - r
2_keras: -178.9710 - val_loss: 4062.7393 - val_r2_keras: -210.6710
Epoch 4/250
52/52 [==============================] - 0s 2ms/step - loss: 3870.9942 - r
2_keras: -148.7229 - val_loss: 3337.2964 - val_r2_keras: -173.3043
Epoch 5/250
52/52 [==============================] - 0s 2ms/step - loss: 2965.3620 - r
2_keras: -123.6781 - val_loss: 2291.5000 - val_r2_keras: -119.2825
Epoch 6/250
52/52 [==============================] - 0s 2ms/step - loss: 1813.5777 - r
2_keras: -67.5155 - val_loss: 1122.9172 - val_r2_keras: -58.6912
Epoch 7/250
52/52 [==============================] - 0s 2ms/step - loss: 697.9330 - r2
_keras: -25.0293 - val_loss: 229.9029 - val_r2_keras: -11.7869
Epoch 8/250
52/52 [==============================] - 0s 2ms/step - loss: 92.4016 - r2_
keras: -2.3772 - val_loss: 64.5237 - val_r2_keras: -2.0057
Epoch 9/250
52/52 [==============================] - 0s 2ms/step - loss: 132.3226 - r2
_keras: -4.1645 - val_loss: 103.1831 - val_r2_keras: -3.7189
Epoch 10/250
52/52 [==============================] - 0s 2ms/step - loss: 89.3743 - r2_
keras: -2.3332 - val_loss: 31.1861 - val_r2_keras: -0.5226
```

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Epoch 11/250
52/52 [==============================] - 0s 2ms/step - loss: 33.8189 - r2_
keras: -0.3422 - val_loss: 39.4365 - val_r2_keras: -1.2734
Epoch 12/250
52/52 [==============================] - 0s 2ms/step - loss: 42.4175 - r2_
keras: -0.7257 - val_loss: 43.9072 - val_r2_keras: -1.5330
Epoch 13/250
52/52 [==============================] - 0s 2ms/step - loss: 37.3059 - r2_
keras: -0.6792 - val_loss: 30.4395 - val_r2_keras: -0.6922
Epoch 14/250
52/52 [==============================] - 0s 2ms/step - loss: 30.0827 - r2_
keras: -0.1920 - val_loss: 26.3629 - val_r2_keras: -0.3460
Epoch 15/250
52/52 [==============================] - 0s 2ms/step - loss: 30.3398 - r2_
keras: -0.1882 - val_loss: 25.9008 - val_r2_keras: -0.3109
Epoch 16/250
52/52 [==============================] - 0s 2ms/step - loss: 29.7140 - r2_
keras: -0.1354 - val_loss: 25.4180 - val_r2_keras: -0.3216
Epoch 17/250
52/52 [==============================] - 0s 2ms/step - loss: 28.8318 - r2_
keras: -0.6080 - val_loss: 25.7322 - val_r2_keras: -0.3749
Epoch 18/250
52/52 [==============================] - 0s 1ms/step - loss: 28.2628 - r2_
keras: -0.1327 - val_loss: 24.8764 - val_r2_keras: -0.3114
Epoch 19/250
52/52 [==============================] - 0s 2ms/step - loss: 27.7166 - r2_
keras: -0.0601 - val_loss: 24.3445 - val_r2_keras: -0.2825
Epoch 20/250
52/52 [==============================] - 0s 2ms/step - loss: 27.5463 - r2_
keras: -0.0690 - val_loss: 24.1873 - val_r2_keras: -0.2935
Epoch 21/250
52/52 [==============================] - ETA: 0s - loss: 26.8906 - r2_kera
s: -0.04 - 0s 1ms/step - loss: 27.1174 - r2_keras: -0.0599 - val_loss: 23.
3310 - val_r2_keras: -0.2259
Epoch 22/250
52/52 [==============================] - 0s 1ms/step - loss: 26.6822 - r2_
keras: -0.0335 - val_loss: 23.0143 - val_r2_keras: -0.2176
Epoch 23/250
52/52 [==============================] - 0s 2ms/step - loss: 26.3340 - r2_
keras: -0.0635 - val_loss: 22.6950 - val_r2_keras: -0.1974
Epoch 24/250
52/52 [==============================] - 0s 2ms/step - loss: 26.1110 - r2_
keras: -0.0154 - val_loss: 22.4216 - val_r2_keras: -0.1854
Epoch 25/250
52/52 [==============================] - 0s 2ms/step - loss: 25.7752 - r2_
keras: -0.0252 - val_loss: 22.0676 - val_r2_keras: -0.1567
Epoch 26/250
52/52 [==============================] - 0s 1ms/step - loss: 25.5159 - r2_
keras: 6.8980e-04 - val_loss: 21.7823 - val_r2_keras: -0.1387
Epoch 27/250
52/52 [==============================] - 0s 1ms/step - loss: 25.3340 - r2_
keras: 0.0059 - val_loss: 21.4682 - val_r2_keras: -0.1156
Epoch 28/250
52/52 [==============================] - 0s 2ms/step - loss: 25.1279 - r2_
keras: -0.0037 - val_loss: 21.2487 - val_r2_keras: -0.1059
Epoch 29/250
52/52 [==============================] - 0s 2ms/step - loss: 24.7921 - r2_
keras: -0.0115 - val_loss: 21.3046 - val_r2_keras: -0.1287
Epoch 30/250
52/52 [==============================] - 0s 2ms/step - loss: 24.7060 - r2_
keras: 0.0072 - val_loss: 20.9058 - val_r2_keras: -0.1031
```

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Epoch 31/250
52/52 [==============================] - 0s 2ms/step - loss: 24.0790 - r2_
keras: 0.0171 - val_loss: 20.3845 - val_r2_keras: -0.0549
Epoch 32/250
52/52 [==============================] - 0s 2ms/step - loss: 24.0980 - r2_
keras: 0.0190 - val_loss: 20.3154 - val_r2_keras: -0.0540
Epoch 33/250
52/52 [==============================] - 0s 2ms/step - loss: 23.8555 - r2_
keras: -0.1368 - val_loss: 20.0117 - val_r2_keras: -0.0539
Epoch 34/250
52/52 [==============================] - 0s 2ms/step - loss: 23.3623 - r2_
keras: 0.0749 - val_loss: 19.6307 - val_r2_keras: -0.0104
Epoch 35/250
52/52 [==============================] - 0s 2ms/step - loss: 22.8774 - r2_
keras: 0.1361 - val_loss: 19.3502 - val_r2_keras: -0.0068
Epoch 36/250
52/52 [==============================] - 0s 2ms/step - loss: 22.6892 - r2_
keras: 0.1215 - val_loss: 19.1621 - val_r2_keras: 0.0087
Epoch 37/250
52/52 [==============================] - 0s 2ms/step - loss: 22.6125 - r2_
keras: 0.0752 - val_loss: 18.8484 - val_r2_keras: 0.0229
Epoch 38/250
52/52 [==============================] - 0s 2ms/step - loss: 21.8972 - r2_
keras: 0.1503 - val_loss: 18.4450 - val_r2_keras: 0.0566
Epoch 39/250
52/52 [==============================] - 0s 2ms/step - loss: 22.2501 - r2_
keras: 0.0991 - val_loss: 18.2637 - val_r2_keras: 0.0540
Epoch 40/250
52/52 [==============================] - 0s 2ms/step - loss: 21.6546 - r2_
keras: 0.1215 - val_loss: 18.1229 - val_r2_keras: 0.0878
Epoch 41/250
52/52 [==============================] - 0s 2ms/step - loss: 21.2581 - r2_
keras: 0.1288 - val_loss: 18.0805 - val_r2_keras: 0.0786
Epoch 42/250
52/52 [==============================] - 0s 2ms/step - loss: 20.9493 - r2_
keras: 0.1562 - val_loss: 17.8067 - val_r2_keras: 0.0699
Epoch 43/250
52/52 [==============================] - 0s 2ms/step - loss: 20.7317 - r2_
keras: 0.1167 - val_loss: 17.4023 - val_r2_keras: 0.0979
Epoch 44/250
52/52 [==============================] - 0s 2ms/step - loss: 20.6054 - r2_
keras: 0.1968 - val_loss: 17.3854 - val_r2_keras: 0.1389
Epoch 45/250
52/52 [==============================] - 0s 1ms/step - loss: 20.3284 - r2_
keras: 0.1375 - val_loss: 16.9796 - val_r2_keras: 0.1437
Epoch 46/250
52/52 [==============================] - ETA: 0s - loss: 19.7973 - r2_kera
s: 0.175 - 0s 2ms/step - loss: 19.7933 - r2_keras: 0.2015 - val_loss: 16.9
069 - val_r2_keras: 0.1292
Epoch 47/250
52/52 [==============================] - 0s 2ms/step - loss: 19.5492 - r2_
keras: 0.2447 - val_loss: 16.5059 - val_r2_keras: 0.1580
Epoch 48/250
52/52 [==============================] - 0s 2ms/step - loss: 19.1236 - r2_
keras: 0.2367 - val_loss: 16.5068 - val_r2_keras: 0.1764
Epoch 49/250
52/52 [==============================] - 0s 2ms/step - loss: 18.6854 - r2_
keras: 0.2696 - val_loss: 16.0378 - val_r2_keras: 0.1927
Epoch 50/250
52/52 [==============================] - ETA: 0s - loss: 18.6625 - r2_kera
s: 0.211 - 0s 1ms/step - loss: 18.6136 - r2_keras: 0.2757 - val_loss: 15.8
```

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434 - val_r2_keras: 0.1869
Epoch 51/250
52/52 [==============================] - 0s 2ms/step - loss: 18.1619 - r2_
keras: 0.2660 - val_loss: 15.3704 - val_r2_keras: 0.2290
Epoch 52/250
52/52 [==============================] - 0s 2ms/step - loss: 17.6762 - r2_
keras: 0.3026 - val_loss: 15.1380 - val_r2_keras: 0.2393
Epoch 53/250
52/52 [==============================] - 0s 2ms/step - loss: 17.3201 - r2_
keras: 0.3018 - val_loss: 14.9589 - val_r2_keras: 0.2493
Epoch 54/250
52/52 [==============================] - 0s 2ms/step - loss: 16.9165 - r2_
keras: 0.3360 - val_loss: 14.5616 - val_r2_keras: 0.2701
Epoch 55/250
52/52 [==============================] - 0s 2ms/step - loss: 16.5051 - r2_
keras: 0.3579 - val_loss: 14.1843 - val_r2_keras: 0.2878
Epoch 56/250
52/52 [==============================] - 0s 2ms/step - loss: 16.3372 - r2_
keras: 0.3673 - val_loss: 14.0564 - val_r2_keras: 0.3119
Epoch 57/250
52/52 [==============================] - 0s 2ms/step - loss: 16.0784 - r2_
keras: 0.3223 - val_loss: 13.3749 - val_r2_keras: 0.3277
Epoch 58/250
52/52 [==============================] - 0s 2ms/step - loss: 15.0570 - r2_
keras: 0.3826 - val_loss: 13.5820 - val_r2_keras: 0.3319
Epoch 59/250
52/52 [==============================] - 0s 2ms/step - loss: 14.6756 - r2_
keras: 0.4281 - val_loss: 12.6999 - val_r2_keras: 0.3584
Epoch 60/250
52/52 [==============================] - 0s 2ms/step - loss: 14.2245 - r2_
keras: 0.4491 - val_loss: 12.2433 - val_r2_keras: 0.3977
Epoch 61/250
52/52 [==============================] - 0s 2ms/step - loss: 13.6554 - r2_
keras: 0.4673 - val_loss: 12.1147 - val_r2_keras: 0.4039
Epoch 62/250
52/52 [==============================] - 0s 2ms/step - loss: 13.3372 - r2_
keras: 0.4589 - val_loss: 11.7299 - val_r2_keras: 0.4170
Epoch 63/250
52/52 [==============================] - 0s 2ms/step - loss: 12.8514 - r2_
keras: 0.4910 - val_loss: 11.3358 - val_r2_keras: 0.4468
Epoch 64/250
52/52 [==============================] - 0s 2ms/step - loss: 12.3096 - r2_
keras: 0.5173 - val_loss: 10.7750 - val_r2_keras: 0.4614
Epoch 65/250
52/52 [==============================] - 0s 2ms/step - loss: 11.9940 - r2_
keras: 0.5431 - val_loss: 10.5035 - val_r2_keras: 0.4766
Epoch 66/250
52/52 [==============================] - 0s 2ms/step - loss: 11.6938 - r2_
keras: 0.5224 - val_loss: 10.2222 - val_r2_keras: 0.4995
Epoch 67/250
52/52 [==============================] - 0s 2ms/step - loss: 11.1913 - r2_
keras: 0.5458 - val_loss: 9.6396 - val_r2_keras: 0.5247
Epoch 68/250
52/52 [==============================] - 0s 2ms/step - loss: 11.0152 - r2_
keras: 0.5624 - val_loss: 9.6590 - val_r2_keras: 0.5168
Epoch 69/250
52/52 [==============================] - 0s 2ms/step - loss: 10.5394 - r2_
keras: 0.5603 - val_loss: 9.1410 - val_r2_keras: 0.5331
Epoch 70/250
52/52 [==============================] - 0s 2ms/step - loss: 10.1234 - r2_
keras: 0.5853 - val_loss: 8.8468 - val_r2_keras: 0.5719
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Epoch 71/250
52/52 [==============================] - 0s 2ms/step - loss: 9.5326 - r2_k
eras: 0.6154 - val_loss: 8.4389 - val_r2_keras: 0.5883
Epoch 72/250
52/52 [==============================] - 0s 2ms/step - loss: 9.1592 - r2_k
eras: 0.6431 - val_loss: 8.0865 - val_r2_keras: 0.6057
Epoch 73/250
52/52 [==============================] - 0s 2ms/step - loss: 8.9246 - r2_k
eras: 0.6257 - val_loss: 7.8489 - val_r2_keras: 0.6073
Epoch 74/250
52/52 [==============================] - 0s 2ms/step - loss: 8.4906 - r2_k
eras: 0.5967 - val_loss: 7.6130 - val_r2_keras: 0.6170
Epoch 75/250
52/52 [==============================] - 0s 1ms/step - loss: 8.0091 - r2_k
eras: 0.6874 - val_loss: 6.8815 - val_r2_keras: 0.6644
Epoch 76/250
52/52 [==============================] - 0s 2ms/step - loss: 7.8152 - r2_k
eras: 0.6997 - val_loss: 6.8541 - val_r2_keras: 0.6632
Epoch 77/250
52/52 [==============================] - 0s 1ms/step - loss: 7.4316 - r2_k
eras: 0.7045 - val_loss: 6.3853 - val_r2_keras: 0.6839
Epoch 78/250
52/52 [==============================] - 0s 2ms/step - loss: 7.2204 - r2_k
eras: 0.7002 - val_loss: 6.1531 - val_r2_keras: 0.6926
Epoch 79/250
52/52 [==============================] - ETA: 0s - loss: 6.9084 - r2_kera
s: 0.72 - 0s 2ms/step - loss: 6.9855 - r2_keras: 0.7328 - val_loss: 6.3399
- val_r2_keras: 0.6788
Epoch 80/250
52/52 [==============================] - 0s 2ms/step - loss: 6.5544 - r2_k
eras: 0.7389 - val_loss: 5.4858 - val_r2_keras: 0.7203
Epoch 81/250
52/52 [==============================] - 0s 2ms/step - loss: 6.2679 - r2_k
eras: 0.7494 - val_loss: 5.5942 - val_r2_keras: 0.7219
Epoch 82/250
52/52 [==============================] - 0s 2ms/step - loss: 6.0031 - r2_k
eras: 0.7631 - val_loss: 4.9343 - val_r2_keras: 0.7548
Epoch 83/250
52/52 [==============================] - 0s 2ms/step - loss: 5.5382 - r2_k
eras: 0.7850 - val_loss: 4.9284 - val_r2_keras: 0.7460
Epoch 84/250
52/52 [==============================] - 0s 2ms/step - loss: 5.2959 - r2_k
eras: 0.7897 - val_loss: 4.7382 - val_r2_keras: 0.7594
Epoch 85/250
52/52 [==============================] - 0s 2ms/step - loss: 4.8601 - r2_k
eras: 0.8086 - val_loss: 3.9201 - val_r2_keras: 0.8016
Epoch 86/250
52/52 [==============================] - 0s 1ms/step - loss: 4.6981 - r2_k
eras: 0.8100 - val_loss: 4.0268 - val_r2_keras: 0.7968
Epoch 87/250
52/52 [==============================] - 0s 2ms/step - loss: 4.4317 - r2_k
eras: 0.8226 - val_loss: 3.6904 - val_r2_keras: 0.8134
Epoch 88/250
52/52 [==============================] - 0s 2ms/step - loss: 4.2584 - r2_k
eras: 0.8351 - val_loss: 3.6334 - val_r2_keras: 0.8165
Epoch 89/250
52/52 [==============================] - 0s 1ms/step - loss: 4.0250 - r2_k
eras: 0.8158 - val_loss: 3.7179 - val_r2_keras: 0.8147
Epoch 90/250
52/52 [==============================] - 0s 2ms/step - loss: 3.7907 - r2_k
eras: 0.8302 - val_loss: 3.2353 - val_r2_keras: 0.8406
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Epoch 91/250
52/52 [==============================] - 0s 2ms/step - loss: 3.6467 - r2_k
eras: 0.8553 - val_loss: 3.2736 - val_r2_keras: 0.8400
Epoch 92/250
52/52 [==============================] - 0s 2ms/step - loss: 3.4728 - r2_k
eras: 0.8620 - val_loss: 3.0969 - val_r2_keras: 0.8453
Epoch 93/250
52/52 [==============================] - 0s 2ms/step - loss: 3.3944 - r2_k
eras: 0.8654 - val_loss: 3.0269 - val_r2_keras: 0.8476
Epoch 94/250
52/52 [==============================] - 0s 2ms/step - loss: 3.2624 - r2_k
eras: 0.8351 - val_loss: 2.8167 - val_r2_keras: 0.8552
Epoch 95/250
52/52 [==============================] - 0s 2ms/step - loss: 3.0852 - r2_k
eras: 0.8826 - val_loss: 2.9950 - val_r2_keras: 0.8568
Epoch 96/250
52/52 [==============================] - 0s 2ms/step - loss: 3.0191 - r2_k
eras: 0.8744 - val_loss: 2.9050 - val_r2_keras: 0.8584
Epoch 97/250
52/52 [==============================] - 0s 2ms/step - loss: 2.9468 - r2_k
eras: 0.8809 - val_loss: 2.8334 - val_r2_keras: 0.8621
Epoch 98/250
52/52 [==============================] - 0s 2ms/step - loss: 2.8188 - r2_k
eras: 0.8854 - val_loss: 2.4935 - val_r2_keras: 0.8741
Epoch 99/250
52/52 [==============================] - 0s 2ms/step - loss: 2.8470 - r2_k
eras: 0.8810 - val_loss: 2.5814 - val_r2_keras: 0.8717
Epoch 100/250
52/52 [==============================] - 0s 2ms/step - loss: 2.7549 - r2_k
eras: 0.8855 - val_loss: 2.8041 - val_r2_keras: 0.8598
Epoch 101/250
52/52 [==============================] - 0s 2ms/step - loss: 2.6905 - r2_k
eras: 0.8892 - val_loss: 2.3674 - val_r2_keras: 0.8834
Epoch 102/250
52/52 [==============================] - 0s 2ms/step - loss: 2.5313 - r2_k
eras: 0.8928 - val_loss: 2.6244 - val_r2_keras: 0.8692
Epoch 103/250
52/52 [==============================] - 0s 2ms/step - loss: 2.4339 - r2_k
eras: 0.9031 - val_loss: 2.3567 - val_r2_keras: 0.8841
Epoch 104/250
52/52 [==============================] - 0s 2ms/step - loss: 2.4109 - r2_k
eras: 0.9079 - val_loss: 2.5856 - val_r2_keras: 0.8735
Epoch 105/250
52/52 [==============================] - 0s 2ms/step - loss: 2.3689 - r2_k
eras: 0.9053 - val_loss: 2.5619 - val_r2_keras: 0.8751
Epoch 106/250
52/52 [==============================] - 0s 2ms/step - loss: 2.2968 - r2_k
eras: 0.9058 - val_loss: 2.3551 - val_r2_keras: 0.8883
Epoch 107/250
52/52 [==============================] - 0s 2ms/step - loss: 2.3298 - r2_k
eras: 0.9046 - val_loss: 2.1591 - val_r2_keras: 0.8961
Epoch 108/250
52/52 [==============================] - 0s 2ms/step - loss: 2.2628 - r2_k
eras: 0.9085 - val_loss: 2.7428 - val_r2_keras: 0.8686
Epoch 109/250
52/52 [==============================] - 0s 2ms/step - loss: 2.3120 - r2_k
eras: 0.9134 - val_loss: 2.1856 - val_r2_keras: 0.8946
Epoch 110/250
52/52 [==============================] - 0s 2ms/step - loss: 2.1361 - r2_k
eras: 0.9169 - val_loss: 2.5783 - val_r2_keras: 0.8799
Epoch 111/250
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52/52 [==============================] - 0s 2ms/step - loss: 2.1178 - r2_k
eras: 0.9092 - val_loss: 2.1475 - val_r2_keras: 0.8932
Epoch 112/250
52/52 [==============================] - 0s 2ms/step - loss: 2.0847 - r2_k
eras: 0.9097 - val_loss: 2.3435 - val_r2_keras: 0.8904
Epoch 113/250
52/52 [==============================] - 0s 2ms/step - loss: 2.1012 - r2_k
eras: 0.9145 - val_loss: 2.1262 - val_r2_keras: 0.8943
Epoch 114/250
52/52 [==============================] - 0s 2ms/step - loss: 1.9376 - r2_k
eras: 0.9224 - val_loss: 2.1453 - val_r2_keras: 0.8995
Epoch 115/250
52/52 [==============================] - 0s 2ms/step - loss: 1.9730 - r2_k
eras: 0.9219 - val_loss: 2.1014 - val_r2_keras: 0.9026
Epoch 116/250
52/52 [==============================] - 0s 2ms/step - loss: 1.9107 - r2_k
eras: 0.9185 - val_loss: 1.9841 - val_r2_keras: 0.9059
Epoch 117/250
52/52 [==============================] - ETA: 0s - loss: 1.8976 - r2_kera
s: 0.92 - 0s 2ms/step - loss: 1.8275 - r2_keras: 0.9253 - val_loss: 2.0430
- val_r2_keras: 0.9007
Epoch 118/250
52/52 [==============================] - 0s 2ms/step - loss: 1.8112 - r2_k
eras: 0.9289 - val_loss: 1.9986 - val_r2_keras: 0.9039
Epoch 119/250
52/52 [==============================] - 0s 2ms/step - loss: 1.7368 - r2_k
eras: 0.9304 - val_loss: 2.1326 - val_r2_keras: 0.9007
Epoch 120/250
52/52 [==============================] - 0s 2ms/step - loss: 1.8182 - r2_k
eras: 0.9270 - val_loss: 1.8404 - val_r2_keras: 0.9126
Epoch 121/250
52/52 [==============================] - 0s 2ms/step - loss: 1.7674 - r2_k
eras: 0.9338 - val_loss: 2.3391 - val_r2_keras: 0.8924
Epoch 122/250
52/52 [==============================] - 0s 1ms/step - loss: 1.7273 - r2_k
eras: 0.9318 - val_loss: 1.7054 - val_r2_keras: 0.9168
Epoch 123/250
52/52 [==============================] - 0s 2ms/step - loss: 1.6811 - r2_k
eras: 0.9333 - val_loss: 2.0091 - val_r2_keras: 0.9076
Epoch 124/250
52/52 [==============================] - 0s 2ms/step - loss: 1.6252 - r2_k
eras: 0.9339 - val_loss: 1.8341 - val_r2_keras: 0.9101
Epoch 125/250
52/52 [==============================] - 0s 1ms/step - loss: 1.6073 - r2_k
eras: 0.9327 - val_loss: 2.0236 - val_r2_keras: 0.9061
Epoch 126/250
52/52 [==============================] - 0s 2ms/step - loss: 1.5921 - r2_k
eras: 0.9266 - val_loss: 1.8683 - val_r2_keras: 0.9155
Epoch 127/250
52/52 [==============================] - 0s 2ms/step - loss: 1.5002 - r2_k
eras: 0.9404 - val_loss: 1.8927 - val_r2_keras: 0.9112
Epoch 128/250
52/52 [==============================] - 0s 2ms/step - loss: 1.4950 - r2_k
eras: 0.9415 - val_loss: 1.7194 - val_r2_keras: 0.9165
Epoch 129/250
52/52 [==============================] - 0s 2ms/step - loss: 1.4422 - r2_k
eras: 0.9436 - val_loss: 2.1023 - val_r2_keras: 0.9031
Epoch 130/250
52/52 [==============================] - 0s 2ms/step - loss: 1.4646 - r2_k
eras: 0.9405 - val_loss: 1.6498 - val_r2_keras: 0.9221
Epoch 131/250
```

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52/52 [==============================] - 0s 1ms/step - loss: 1.3899 - r2_k
eras: 0.9485 - val_loss: 1.9629 - val_r2_keras: 0.9093
Epoch 132/250
52/52 [==============================] - 0s 2ms/step - loss: 1.4051 - r2_k
eras: 0.9392 - val_loss: 1.6819 - val_r2_keras: 0.9191
Epoch 133/250
52/52 [==============================] - 0s 2ms/step - loss: 1.3889 - r2_k
eras: 0.9427 - val_loss: 1.9735 - val_r2_keras: 0.9082
Epoch 134/250
52/52 [==============================] - 0s 2ms/step - loss: 1.3378 - r2_k
eras: 0.9486 - val_loss: 1.6265 - val_r2_keras: 0.9220
Epoch 135/250
52/52 [==============================] - 0s 2ms/step - loss: 1.3064 - r2_k
eras: 0.9443 - val_loss: 1.7349 - val_r2_keras: 0.9191
Epoch 136/250
52/52 [==============================] - 0s 2ms/step - loss: 1.2925 - r2_k
eras: 0.9488 - val_loss: 1.8004 - val_r2_keras: 0.9164
Epoch 137/250
52/52 [==============================] - 0s 2ms/step - loss: 1.2492 - r2_k
eras: 0.9453 - val_loss: 1.5870 - val_r2_keras: 0.9230
Epoch 138/250
52/52 [==============================] - 0s 1ms/step - loss: 1.2960 - r2_k
eras: 0.9486 - val_loss: 1.7343 - val_r2_keras: 0.9192
Epoch 139/250
52/52 [==============================] - 0s 2ms/step - loss: 1.2280 - r2_k
eras: 0.9523 - val_loss: 1.5257 - val_r2_keras: 0.9259
Epoch 140/250
52/52 [==============================] - 0s 2ms/step - loss: 1.2428 - r2_k
eras: 0.9508 - val_loss: 1.6901 - val_r2_keras: 0.9201
Epoch 141/250
52/52 [==============================] - 0s 2ms/step - loss: 1.1972 - r2_k
eras: 0.9516 - val_loss: 1.6859 - val_r2_keras: 0.9215
Epoch 142/250
52/52 [==============================] - 0s 2ms/step - loss: 1.1317 - r2_k
eras: 0.9535 - val_loss: 1.4877 - val_r2_keras: 0.9310
Epoch 143/250
52/52 [==============================] - 0s 2ms/step - loss: 1.1330 - r2_k
eras: 0.9559 - val_loss: 1.5974 - val_r2_keras: 0.9248
Epoch 144/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0913 - r2_k
eras: 0.9561 - val_loss: 1.6533 - val_r2_keras: 0.9226
Epoch 145/250
52/52 [==============================] - 0s 2ms/step - loss: 1.1033 - r2_k
eras: 0.9567 - val_loss: 1.8163 - val_r2_keras: 0.9162
Epoch 146/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0959 - r2_k
eras: 0.9558 - val_loss: 1.4404 - val_r2_keras: 0.9311
Epoch 147/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0550 - r2_k
eras: 0.9563 - val_loss: 1.7675 - val_r2_keras: 0.9199
Epoch 148/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0604 - r2_k
eras: 0.9587 - val_loss: 1.5596 - val_r2_keras: 0.9271
Epoch 149/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0065 - r2_k
eras: 0.9602 - val_loss: 1.6200 - val_r2_keras: 0.9240
Epoch 150/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0119 - r2_k
eras: 0.9596 - val_loss: 1.4587 - val_r2_keras: 0.9307
Epoch 151/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0289 - r2_k
```

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eras: 0.9599 - val_loss: 1.5080 - val_r2_keras: 0.9291
Epoch 152/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0566 - r2_k
eras: 0.9582 - val_loss: 1.4638 - val_r2_keras: 0.9313
Epoch 153/250
52/52 [==============================] - 0s 2ms/step - loss: 1.0306 - r2_k
eras: 0.9578 - val_loss: 1.4004 - val_r2_keras: 0.9337
Epoch 154/250
52/52 [==============================] - 0s 2ms/step - loss: 0.9637 - r2_k
eras: 0.9516 - val_loss: 1.5434 - val_r2_keras: 0.9271
Epoch 155/250
52/52 [==============================] - 0s 2ms/step - loss: 0.9574 - r2_k
eras: 0.9626 - val_loss: 1.6603 - val_r2_keras: 0.9244
Epoch 156/250
52/52 [==============================] - 0s 2ms/step - loss: 0.9451 - r2_k
eras: 0.9621 - val_loss: 1.4849 - val_r2_keras: 0.9302
Epoch 157/250
52/52 [==============================] - 0s 2ms/step - loss: 0.9198 - r2_k
eras: 0.9615 - val_loss: 1.6175 - val_r2_keras: 0.9256
Epoch 158/250
52/52 [==============================] - 0s 2ms/step - loss: 0.9189 - r2_k
eras: 0.9627 - val_loss: 1.5668 - val_r2_keras: 0.9262
Epoch 159/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8949 - r2_k
eras: 0.9647 - val_loss: 1.4722 - val_r2_keras: 0.9318
Epoch 160/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8631 - r2_k
eras: 0.9658 - val_loss: 1.5532 - val_r2_keras: 0.9283
Epoch 161/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8647 - r2_k
eras: 0.9663 - val_loss: 1.5368 - val_r2_keras: 0.9299
Epoch 162/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8586 - r2_k
eras: 0.9666 - val_loss: 1.5065 - val_r2_keras: 0.9293
Epoch 163/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8371 - r2_k
eras: 0.9667 - val_loss: 1.5064 - val_r2_keras: 0.9313
Epoch 164/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8427 - r2_k
eras: 0.9671 - val_loss: 1.3891 - val_r2_keras: 0.9355
Epoch 165/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8105 - r2_k
eras: 0.9662 - val_loss: 1.5250 - val_r2_keras: 0.9295
Epoch 166/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8271 - r2_k
eras: 0.9669 - val_loss: 1.4371 - val_r2_keras: 0.9326
Epoch 167/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8092 - r2_k
eras: 0.9678 - val_loss: 1.6408 - val_r2_keras: 0.9260
Epoch 168/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8022 - r2_k
eras: 0.9661 - val_loss: 1.4033 - val_r2_keras: 0.9343
Epoch 169/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8229 - r2_k
eras: 0.9673 - val_loss: 1.4589 - val_r2_keras: 0.9327
Epoch 170/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7699 - r2_k
eras: 0.9694 - val_loss: 1.3712 - val_r2_keras: 0.9352
Epoch 171/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7751 - r2_k
eras: 0.9698 - val_loss: 1.6897 - val_r2_keras: 0.9234
```

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Epoch 172/250
52/52 [==============================] - 0s 2ms/step - loss: 0.8105 - r2_k
eras: 0.9674 - val_loss: 1.4438 - val_r2_keras: 0.9323
Epoch 173/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7778 - r2_k
eras: 0.9672 - val_loss: 1.4585 - val_r2_keras: 0.9322
Epoch 174/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7678 - r2_k
eras: 0.9676 - val_loss: 1.5884 - val_r2_keras: 0.9284
Epoch 175/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7721 - r2_k
eras: 0.9697 - val_loss: 1.4907 - val_r2_keras: 0.9315
Epoch 176/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7562 - r2_k
eras: 0.9703 - val_loss: 1.3547 - val_r2_keras: 0.9361
Epoch 177/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7291 - r2_k
eras: 0.9709 - val_loss: 1.3779 - val_r2_keras: 0.9368
Epoch 178/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7118 - r2_k
eras: 0.9714 - val_loss: 1.5184 - val_r2_keras: 0.9305
Epoch 179/250
52/52 [==============================] - ETA: 0s - loss: 0.7132 - r2_kera
s: 0.97 - 0s 2ms/step - loss: 0.7180 - r2_keras: 0.9718 - val_loss: 1.3735
- val_r2_keras: 0.9351
Epoch 180/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7034 - r2_k
eras: 0.9715 - val_loss: 1.3780 - val_r2_keras: 0.9364
Epoch 181/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7072 - r2_k
eras: 0.9701 - val_loss: 1.4218 - val_r2_keras: 0.9351
Epoch 182/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7057 - r2_k
eras: 0.9722 - val_loss: 1.5191 - val_r2_keras: 0.9297
Epoch 183/250
52/52 [==============================] - ETA: 0s - loss: 0.6757 - r2_kera
s: 0.97 - 0s 2ms/step - loss: 0.6874 - r2_keras: 0.9725 - val_loss: 1.4328
- val_r2_keras: 0.9340
Epoch 184/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6858 - r2_k
eras: 0.9731 - val_loss: 1.3261 - val_r2_keras: 0.9376
Epoch 185/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7005 - r2_k
eras: 0.9711 - val_loss: 1.5810 - val_r2_keras: 0.9286
Epoch 186/250
52/52 [==============================] - 0s 2ms/step - loss: 0.7004 - r2_k
eras: 0.9721 - val_loss: 1.4440 - val_r2_keras: 0.9326
Epoch 187/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6704 - r2_k
eras: 0.9750 - val_loss: 1.3528 - val_r2_keras: 0.9367
Epoch 188/250
52/52 [==============================] - 0s 1ms/step - loss: 0.6557 - r2_k
eras: 0.9723 - val_loss: 1.4664 - val_r2_keras: 0.9333
Epoch 189/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6969 - r2_k
eras: 0.9721 - val_loss: 1.3444 - val_r2_keras: 0.9365
Epoch 190/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6507 - r2_k
eras: 0.9743 - val_loss: 1.4847 - val_r2_keras: 0.9322
Epoch 191/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6367 - r2_k
```

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eras: 0.9725 - val_loss: 1.4230 - val_r2_keras: 0.9343
Epoch 192/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6413 - r2_k
eras: 0.9752 - val_loss: 1.2174 - val_r2_keras: 0.9424
Epoch 193/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6616 - r2_k
eras: 0.9743 - val_loss: 1.5336 - val_r2_keras: 0.9305
Epoch 194/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6719 - r2_k
eras: 0.9740 - val_loss: 1.4300 - val_r2_keras: 0.9343
Epoch 195/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6667 - r2_k
eras: 0.9728 - val_loss: 1.3128 - val_r2_keras: 0.9372
Epoch 196/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6924 - r2_k
eras: 0.9722 - val_loss: 1.5012 - val_r2_keras: 0.9316
Epoch 197/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6626 - r2_k
eras: 0.9731 - val_loss: 1.4150 - val_r2_keras: 0.9349
Epoch 198/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6356 - r2_k
eras: 0.9750 - val_loss: 1.2906 - val_r2_keras: 0.9392
Epoch 199/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6182 - r2_k
eras: 0.9726 - val_loss: 1.5461 - val_r2_keras: 0.9290
Epoch 200/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6483 - r2_k
eras: 0.9721 - val_loss: 1.3408 - val_r2_keras: 0.9381
Epoch 201/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6069 - r2_k
eras: 0.9765 - val_loss: 1.3454 - val_r2_keras: 0.9364
Epoch 202/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6390 - r2_k
eras: 0.9744 - val_loss: 1.4492 - val_r2_keras: 0.9339
Epoch 203/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6365 - r2_k
eras: 0.9749 - val_loss: 1.3631 - val_r2_keras: 0.9361
Epoch 204/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6082 - r2_k
eras: 0.9755 - val_loss: 1.3802 - val_r2_keras: 0.9360
Epoch 205/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6486 - r2_k
eras: 0.9739 - val_loss: 1.4299 - val_r2_keras: 0.9325
Epoch 206/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6061 - r2_k
eras: 0.9759 - val_loss: 1.3633 - val_r2_keras: 0.9376
Epoch 207/250
52/52 [==============================] - 0s 2ms/step - loss: 0.6017 - r2_k
eras: 0.9763 - val_loss: 1.2971 - val_r2_keras: 0.9395
Epoch 208/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5565 - r2_k
eras: 0.9783 - val_loss: 1.3319 - val_r2_keras: 0.9382
Epoch 209/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5594 - r2_k
eras: 0.9760 - val_loss: 1.4730 - val_r2_keras: 0.9331
Epoch 210/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5675 - r2_k
eras: 0.9759 - val_loss: 1.2157 - val_r2_keras: 0.9428
Epoch 211/250
52/52 [==============================] - 0s 1ms/step - loss: 0.5753 - r2_k
eras: 0.9763 - val_loss: 1.4100 - val_r2_keras: 0.9352
```

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Epoch 212/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5900 - r2_k
eras: 0.9764 - val_loss: 1.4470 - val_r2_keras: 0.9344
Epoch 213/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5769 - r2_k
eras: 0.9774 - val_loss: 1.2558 - val_r2_keras: 0.9392
Epoch 214/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5725 - r2_k
eras: 0.9751 - val_loss: 1.5256 - val_r2_keras: 0.9292
Epoch 215/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5624 - r2_k
eras: 0.9772 - val_loss: 1.3690 - val_r2_keras: 0.9371
Epoch 216/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5409 - r2_k
eras: 0.9779 - val_loss: 1.2629 - val_r2_keras: 0.9413
Epoch 217/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5312 - r2_k
eras: 0.9784 - val_loss: 1.3537 - val_r2_keras: 0.9367
Epoch 218/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5340 - r2_k
eras: 0.9774 - val_loss: 1.3441 - val_r2_keras: 0.9374
Epoch 219/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5404 - r2_k
eras: 0.9777 - val_loss: 1.3027 - val_r2_keras: 0.9388
Epoch 220/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5217 - r2_k
eras: 0.9794 - val_loss: 1.4617 - val_r2_keras: 0.9332
Epoch 221/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5219 - r2_k
eras: 0.9793 - val_loss: 1.3080 - val_r2_keras: 0.9387
Epoch 222/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5302 - r2_k
eras: 0.9781 - val_loss: 1.3636 - val_r2_keras: 0.9382
Epoch 223/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5130 - r2_k
eras: 0.9796 - val_loss: 1.3667 - val_r2_keras: 0.9352
Epoch 224/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5338 - r2_k
eras: 0.9786 - val_loss: 1.3495 - val_r2_keras: 0.9380
Epoch 225/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5523 - r2_k
eras: 0.9732 - val_loss: 1.3545 - val_r2_keras: 0.9378
Epoch 226/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5641 - r2_k
eras: 0.9782 - val_loss: 1.3354 - val_r2_keras: 0.9362
Epoch 227/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5294 - r2_k
eras: 0.9797 - val_loss: 1.4138 - val_r2_keras: 0.9345
Epoch 228/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5360 - r2_k
eras: 0.9783 - val_loss: 1.3434 - val_r2_keras: 0.9385
Epoch 229/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5308 - r2_k
eras: 0.9800 - val_loss: 1.4137 - val_r2_keras: 0.9342
Epoch 230/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5072 - r2_k
eras: 0.9783 - val_loss: 1.3080 - val_r2_keras: 0.9384
Epoch 231/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5402 - r2_k
eras: 0.9790 - val_loss: 1.3541 - val_r2_keras: 0.9369
Epoch 232/250
```

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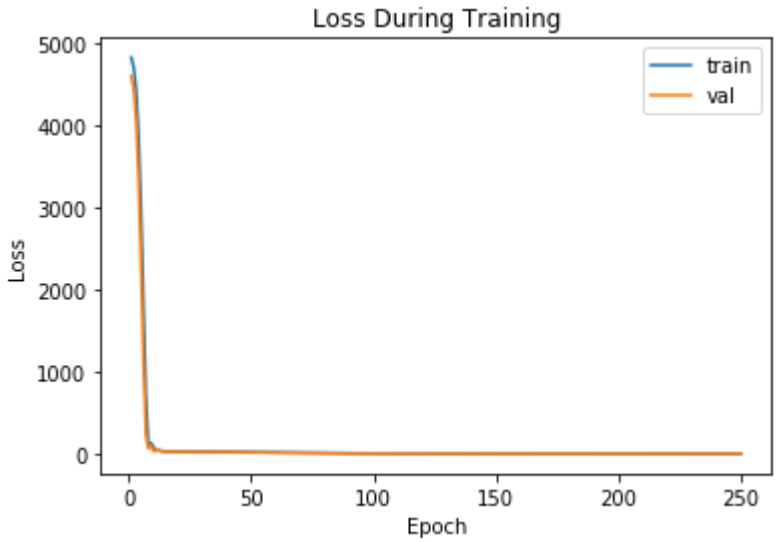
52/52 [==============================] - 0s 1ms/step - loss: 0.5138 - r2_k
eras: 0.9800 - val_loss: 1.3768 - val_r2_keras: 0.9368
Epoch 233/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5213 - r2_k
eras: 0.9799 - val_loss: 1.2984 - val_r2_keras: 0.9392
Epoch 234/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5097 - r2_k
eras: 0.9806 - val_loss: 1.3485 - val_r2_keras: 0.9371
Epoch 235/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5040 - r2_k
eras: 0.9801 - val_loss: 1.3175 - val_r2_keras: 0.9400
Epoch 236/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5130 - r2_k
eras: 0.9786 - val_loss: 1.4232 - val_r2_keras: 0.9337
Epoch 237/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5324 - r2_k
eras: 0.9774 - val_loss: 1.3542 - val_r2_keras: 0.9351
Epoch 238/250
52/52 [==============================] - 0s 1ms/step - loss: 0.5427 - r2_k
eras: 0.9795 - val_loss: 1.3043 - val_r2_keras: 0.9385
Epoch 239/250
52/52 [==============================] - ETA: 0s - loss: 0.5560 - r2_kera
s: 0.97 - 0s 2ms/step - loss: 0.4950 - r2_keras: 0.9799 - val_loss: 1.4213
- val_r2_keras: 0.9354
Epoch 240/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4836 - r2_k
eras: 0.9778 - val_loss: 1.2655 - val_r2_keras: 0.9412
Epoch 241/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5102 - r2_k
eras: 0.9788 - val_loss: 1.2972 - val_r2_keras: 0.9393
Epoch 242/250
52/52 [==============================] - 0s 2ms/step - loss: 0.5009 - r2_k
eras: 0.9804 - val_loss: 1.3320 - val_r2_keras: 0.9377
Epoch 243/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4854 - r2_k
eras: 0.9810 - val_loss: 1.2780 - val_r2_keras: 0.9406
Epoch 244/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4830 - r2_k
eras: 0.9815 - val_loss: 1.2657 - val_r2_keras: 0.9403
Epoch 245/250
52/52 [==============================] - ETA: 0s - loss: 0.5045 - r2_kera
s: 0.98 - 0s 2ms/step - loss: 0.5048 - r2_keras: 0.9803 - val_loss: 1.5320
- val_r2_keras: 0.9299
Epoch 246/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4860 - r2_k
eras: 0.9815 - val_loss: 1.3054 - val_r2_keras: 0.9385
Epoch 247/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4893 - r2_k
eras: 0.9812 - val_loss: 1.1847 - val_r2_keras: 0.9445
Epoch 248/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4852 - r2_k
eras: 0.9797 - val_loss: 1.3623 - val_r2_keras: 0.9370
Epoch 249/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4793 - r2_k
eras: 0.9803 - val_loss: 1.4467 - val_r2_keras: 0.9346
Epoch 250/250
52/52 [==============================] - 0s 2ms/step - loss: 0.4902 - r2_k
eras: 0.9804 - val_loss: 1.2515 - val_r2_keras: 0.9392
Train Score: 0.66 MSE (0.81 RMSE)
Test Score: 1.35 MSE (1.16 RMSE)
```

In [123]:

```
plot_model_history(history)
```



Prediction and Plot

In [124]:

```
# Forecast predictions
forecastPlot = np.zeros((len(emission_data) + horizon))
forecastPlot[:] = np.nan

# Features
#X = np.zeros((1, look_back, feature_data.shape[1]))
X = np.zeros((1, look_back, num_of_feats))
#X[0] = feature_data[len(feature_data)-look_back:, :]
X[0] = feature_data[len(feature_data)-look_back:, :num_of_feats]
predict = model.predict(X)
forecastPlot[len(feature_data):len(feature_data)+horizon] = predict[:]

print(f"Forecast: {predict}")

# Plot baseline, training, test and forecast
plt.plot(emission_data[:])
plt.plot(trainPredictPlot[:])
plt.plot(testPredictPlot[:])
plt.plot(forecastPlot[:])
plt.show()
```

```
Forecast: [[70.526474 68.96372  65.73839  61.481346 58.773514 57.567326]]
```