rnn_weather_pred

October 15, 2024

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import matplotlib.pyplot as plt
```

[2]:
```
df = pd.read_csv('seattle-weather.xls')
df.head()
```

[2]:
```
         date  precipitation  temp_max  temp_min  wind  weather
0  2012-01-01            0.0      12.8       5.0   4.7  drizzle
1  2012-01-02           10.9      10.6       2.8   4.5     rain
2  2012-01-03            0.8      11.7       7.2   2.3     rain
3  2012-01-04           20.3      12.2       5.6   4.7     rain
4  2012-01-05            1.3       8.9       2.8   6.1     rain
```

[3]:
```
df.isnull().sum()
```

[3]:
```
date             0
precipitation    0
temp_max         0
temp_min         0
wind             0
weather          0
dtype: int64
```

[4]:
```
#  Pandas DataFrame
df.duplicated().sum()
```

[4]: 0

[5]:
```
#column Open converted into numpy array
training_set = df.iloc[:,2:3].values
training_set
```

[5]:
```
array([[12.8],
       [10.6],
       [11.7],
```

```
         …,
         [ 7.2],
         [ 5.6],
         [ 5.6]])
```

[6]:
```
len(training_set)
amp = max(training_set)
print(amp)
```

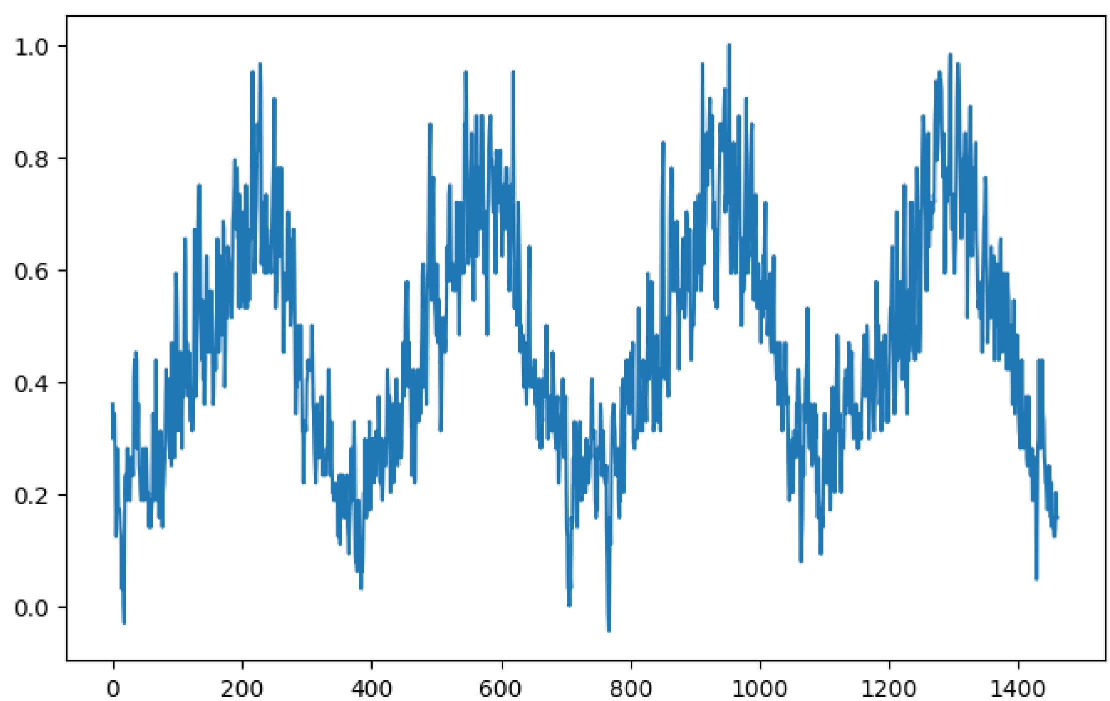
```
[35.6]
```

[7]:
```
training_set =training_set/amp
training_set
```

[7]:
```
array([[0.35955056],
       [0.29775281],
       [0.32865169],
       …,
       [0.20224719],
       [0.15730337],
       [0.15730337]])
```

[8]:
```
fig1=plt.figure(figsize=(8,5))
plt.plot(training_set)
```

[8]:
```
[<matplotlib.lines.Line2D at 0x7f6a23dffcd0>]
```



[9]:
```
#
def df_to_XY(df,window_size=10):
 X_train=[]
 y_train=[]

 for i in range(10,len(training_set)):
    X_train.append(training_set[i-10:i,0])
    y_train.append(training_set[i,0])

 X_train, y_train = np.array(X_train), np.array(y_train)
 return X_train, y_train
```

[10]:
```
WINDOW = 10
X,y = df_to_XY(df,WINDOW)

print(len(X),len(y))
print(X[0],X[1])
```

```
1451 1451
[0.35955056 0.29775281 0.32865169 0.34269663 0.25       0.12359551
 0.20224719 0.28089888 0.26404494 0.17134831] [0.29775281 0.32865169 0.34269663
0.25       0.12359551 0.20224719
 0.28089888 0.26404494 0.17134831 0.17134831]
```

[11]:
```
#           RNN/LSTM/GRU
X_train = np.reshape(X,(X.shape[0],X.shape[1],1))
X_train = X[:1000]
y_train = y[:1000]

X_test = X[1000:]
y_test = y[1000:]
```

[12]:
```
print(X_train.shape)
```

```
(1000, 10)
```

[13]:
```
#Building the RNN
import keras
from keras.models import Sequential
from keras.layers import Dense, LSTM, Dropout,SimpleRNN
```

[14]:
```
#Addinf the first LSTM layer and some Dropout regularisation
model = Sequential()

model.add(SimpleRNN(units=5,input_shape=(WINDOW,1),activation='relu'))
```

```python
#Output layer
model.add(Dense(units=1,activation="linear"))

model.compile(optimizer='adam',loss='mean_squared_error')
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 simple_rnn (SimpleRNN)      (None, 5)                 35

 dense (Dense)               (None, 1)                 6

=================================================================
Total params: 41
Trainable params: 41
Non-trainable params: 0
_________________________________________________________________
2024-10-15 10:03:21.393193: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.416614: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.416735: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.417531: I tensorflow/core/platform/cpu_feature_guard.cc:151]
This TensorFlow binary is optimized with oneAPI Deep Neural Network Library
(oneDNN) to use the following CPU instructions in performance-critical
operations:  AVX2 FMA
To enable them in other operations, rebuild TensorFlow with the appropriate
compiler flags.
2024-10-15 10:03:21.418915: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.419020: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.419086: I
```

```
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.824465: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.824604: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.824679: I
tensorflow/stream_executor/cuda/cuda_gpu_executor.cc:939] successful NUMA node
read from SysFS had negative value (-1), but there must be at least one NUMA
node, so returning NUMA node zero
2024-10-15 10:03:21.824754: I
tensorflow/core/common_runtime/gpu/gpu_device.cc:1525] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 12150 MB memory:  -> device:
0, name: NVIDIA RTX A4000, pci bus id: 0000:01:00.0, compute capability: 8.6
```

[15]:
```python
from tensorflow.keras.callbacks import ModelCheckpoint,EarlyStopping
from tensorflow.keras.losses import MeanSquaredError
from tensorflow.keras.metrics import RootMeanSquaredError
from tensorflow.keras.optimizers import Adam
```

[16]:
```python
#fitting the rnn to the training set
history=model.fit(X_train,y_train,epochs=100, batch_size=32 ,validation_split=0.
↪2)
```

```
Epoch 1/100
21/25 [========================>…] - ETA: 0s - loss: 0.7099

2024-10-15 10:03:22.944919: I tensorflow/stream_executor/cuda/cuda_blas.cc:1774]
TensorFloat-32 will be used for the matrix multiplication. This will only be
logged once.

25/25 [==============================] - 1s 11ms/step - loss: 0.7054 - val_loss:
1.1718
Epoch 2/100
 1/25 […] - ETA: 0s - loss: 0.6388Epoch 2/100
25/25 [==============================] - 0s 9ms/step - loss: 0.5989 - val_loss:
1.0197
Epoch 3/100
25/25 [==============================] - 0s 10ms/step - loss: 0.5119 - val_loss:
0.8945
Epoch 4/100
25/25 [==============================] - 0s 10ms/step - loss: 0.4414 - val_loss:
0.7875
Epoch 5/100
```

```
25/25 [==============================] - 0s 10ms/step - loss: 0.3824 - val_loss:
0.6969
Epoch 6/100
25/25 [==============================] - 0s 10ms/step - loss: 0.3330 - val_loss:
0.6202
Epoch 7/100
25/25 [==============================] - 0s 10ms/step - loss: 0.2914 - val_loss:
0.5548
Epoch 8/100
25/25 [==============================] - 0s 10ms/step - loss: 0.2567 - val_loss:
0.4971
Epoch 9/100
25/25 [==============================] - 0s 9ms/step - loss: 0.2269 - val_loss:
0.4472
Epoch 10/100
25/25 [==============================] - 0s 9ms/step - loss: 0.2015 - val_loss:
0.4038
Epoch 11/100
25/25 [==============================] - 0s 9ms/step - loss: 0.1799 - val_loss:
0.3654
Epoch 12/100
25/25 [==============================] - 0s 11ms/step - loss: 0.1610 - val_loss:
0.3323
Epoch 13/100
25/25 [==============================] - 0s 9ms/step - loss: 0.1449 - val_loss:
0.3022
Epoch 14/100
25/25 [==============================] - 0s 9ms/step - loss: 0.1306 - val_loss:
0.2764
Epoch 15/100
25/25 [==============================] - 0s 10ms/step - loss: 0.1184 - val_loss:
0.2526
Epoch 16/100
25/25 [==============================] - 0s 9ms/step - loss: 0.1075 - val_loss:
0.2316
Epoch 17/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0980 - val_loss:
0.2125
Epoch 18/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0894 - val_loss:
0.1956
Epoch 19/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0818 - val_loss:
0.1805
Epoch 20/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0751 - val_loss:
0.1663
Epoch 21/100
```

```
25/25 [==============================] - 0s 10ms/step - loss: 0.0690 - val_loss:
0.1535
Epoch 22/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0634 - val_loss:
0.1424
Epoch 23/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0586 - val_loss:
0.1315
Epoch 24/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0541 - val_loss:
0.1220
Epoch 25/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0501 - val_loss:
0.1132
Epoch 26/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0465 - val_loss:
0.1053
Epoch 27/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0432 - val_loss:
0.0982
Epoch 28/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0402 - val_loss:
0.0917
Epoch 29/100
25/25 [==============================] - 0s 7ms/step - loss: 0.0376 - val_loss:
0.0856
Epoch 30/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0351 - val_loss:
0.0802
Epoch 31/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0329 - val_loss:
0.0752
Epoch 32/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0308 - val_loss:
0.0705
Epoch 33/100
25/25 [==============================] - 0s 7ms/step - loss: 0.0290 - val_loss:
0.0663
Epoch 34/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0273 - val_loss:
0.0621
Epoch 35/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0257 - val_loss:
0.0587
Epoch 36/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0243 - val_loss:
0.0554
Epoch 37/100
```

```
25/25 [==============================] - 0s 9ms/step - loss: 0.0230 - val_loss:
0.0524
Epoch 38/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0219 - val_loss:
0.0493
Epoch 39/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0208 - val_loss:
0.0470
Epoch 40/100
25/25 [==============================] - 0s 7ms/step - loss: 0.0198 - val_loss:
0.0445
Epoch 41/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0189 - val_loss:
0.0423
Epoch 42/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0180 - val_loss:
0.0403
Epoch 43/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0172 - val_loss:
0.0385
Epoch 44/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0165 - val_loss:
0.0367
Epoch 45/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0158 - val_loss:
0.0350
Epoch 46/100
25/25 [==============================] - 0s 5ms/step - loss: 0.0152 - val_loss:
0.0335
Epoch 47/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0147 - val_loss:
0.0320
Epoch 48/100
25/25 [==============================] - 0s 4ms/step - loss: 0.0141 - val_loss:
0.0308
Epoch 49/100
25/25 [==============================] - 0s 4ms/step - loss: 0.0136 - val_loss:
0.0295
Epoch 50/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0132 - val_loss:
0.0284
Epoch 51/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0128 - val_loss:
0.0272
Epoch 52/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0124 - val_loss:
0.0263
Epoch 53/100
```

```
25/25 [==============================] - 0s 8ms/step - loss: 0.0120 - val_loss:
0.0253
Epoch 54/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0117 - val_loss:
0.0244
Epoch 55/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0114 - val_loss:
0.0237
Epoch 56/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0111 - val_loss:
0.0228
Epoch 57/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0108 - val_loss:
0.0220
Epoch 58/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0105 - val_loss:
0.0214
Epoch 59/100
25/25 [==============================] - 0s 12ms/step - loss: 0.0103 - val_loss:
0.0207
Epoch 60/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0101 - val_loss:
0.0202
Epoch 61/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0099 - val_loss:
0.0195
Epoch 62/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0097 - val_loss:
0.0190
Epoch 63/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0095 - val_loss:
0.0184
Epoch 64/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0093 - val_loss:
0.0180
Epoch 65/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0091 - val_loss:
0.0175
Epoch 66/100
25/25 [==============================] - 0s 6ms/step - loss: 0.0090 - val_loss:
0.0171
Epoch 67/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0088 - val_loss:
0.0167
Epoch 68/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0087 - val_loss:
0.0164
Epoch 69/100
```

```
25/25 [==============================] - 0s 10ms/step - loss: 0.0086 - val_loss:
0.0159
Epoch 70/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0084 - val_loss:
0.0156
Epoch 71/100
25/25 [==============================] - 0s 4ms/step - loss: 0.0083 - val_loss:
0.0152
Epoch 72/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0082 - val_loss:
0.0151
Epoch 73/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0081 - val_loss:
0.0147
Epoch 74/100
25/25 [==============================] - 0s 12ms/step - loss: 0.0080 - val_loss:
0.0144
Epoch 75/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0079 - val_loss:
0.0142
Epoch 76/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0078 - val_loss:
0.0139
Epoch 77/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0077 - val_loss:
0.0136
Epoch 78/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0077 - val_loss:
0.0134
Epoch 79/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0076 - val_loss:
0.0132
Epoch 80/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0075 - val_loss:
0.0130
Epoch 81/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0074 - val_loss:
0.0128
Epoch 82/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0074 - val_loss:
0.0127
Epoch 83/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0073 - val_loss:
0.0124
Epoch 84/100
25/25 [==============================] - 0s 8ms/step - loss: 0.0072 - val_loss:
0.0123
Epoch 85/100
```

```
25/25 [==============================] - 0s 10ms/step - loss: 0.0072 - val_loss:
0.0121
Epoch 86/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0071 - val_loss:
0.0119
Epoch 87/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0071 - val_loss:
0.0118
Epoch 88/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0071 - val_loss:
0.0116
Epoch 89/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0070 - val_loss:
0.0117
Epoch 90/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0070 - val_loss:
0.0112
Epoch 91/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0069 - val_loss:
0.0111
Epoch 92/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0069 - val_loss:
0.0111
Epoch 93/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0068 - val_loss:
0.0109
Epoch 94/100
25/25 [==============================] - 0s 12ms/step - loss: 0.0068 - val_loss:
0.0109
Epoch 95/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0068 - val_loss:
0.0108
Epoch 96/100
25/25 [==============================] - 0s 10ms/step - loss: 0.0067 - val_loss:
0.0107
Epoch 97/100
25/25 [==============================] - 0s 11ms/step - loss: 0.0067 - val_loss:
0.0104
Epoch 98/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0067 - val_loss:
0.0105
Epoch 99/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0066 - val_loss:
0.0103
Epoch 100/100
25/25 [==============================] - 0s 9ms/step - loss: 0.0066 - val_loss:
0.0103
```

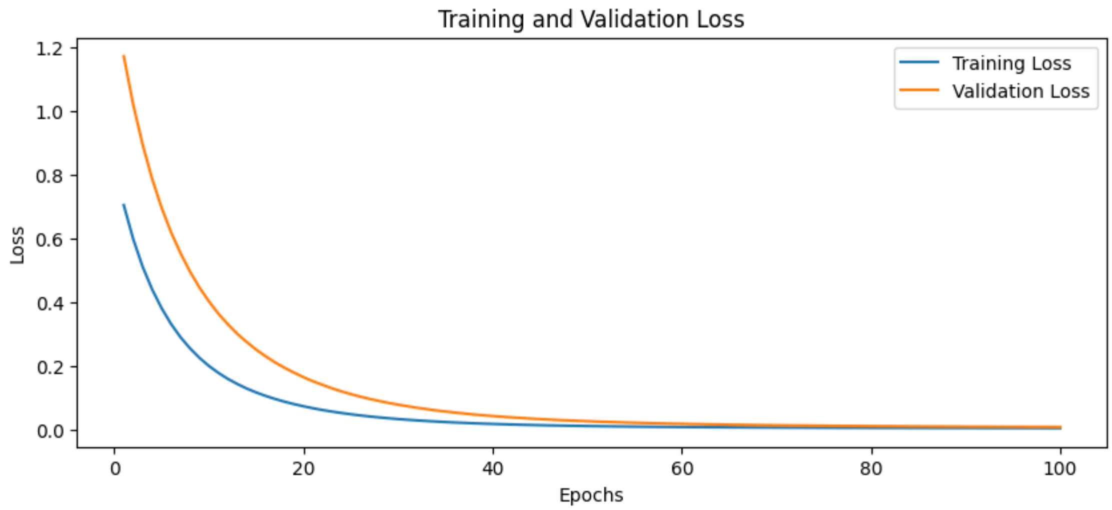
[17]:
```python
his = pd.DataFrame(history.history)
```

[18]:
```python
his.head()
```

[18]:

	loss	val_loss
0	0.705381	1.171797
1	0.598857	1.019666
2	0.511914	0.894542
3	0.441358	0.787542
4	0.382395	0.696939

[19]:
```python
#
history_loss = history.history['loss']
history_val_loss = history.history['val_loss']

#    x     epoch
epochs = range(1, len(history_loss) + 1)

#
plt.figure(figsize=(10, 4))

#
plt.plot(epochs, history_loss, label='Training Loss')

#
plt.plot(epochs, history_val_loss, label='Validation Loss')

#
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

#
plt.show()
```

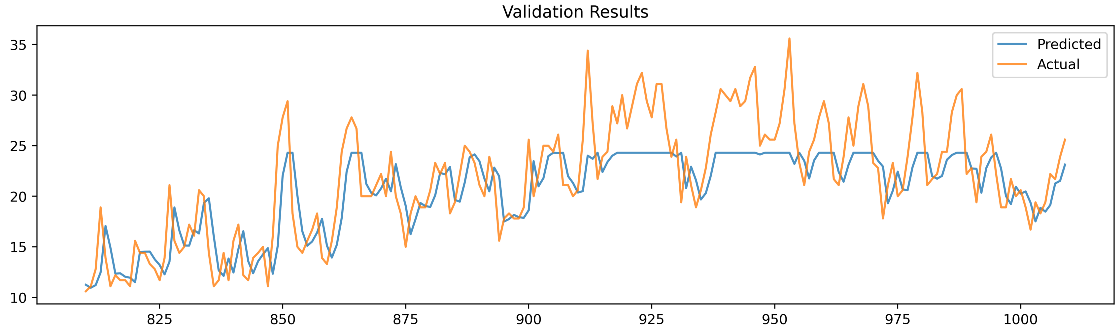


[20]:
```
train_pred = model.predict(X_train)
test_pred = model.predict(X_test)
```

[21]:
```
train_pred=train_pred*amp
test_pred=test_pred*amp
```

[22]:
```
pred = np.concatenate([train_pred,test_pred])
df_pred = pd.DataFrame(df["temp_max"].copy())
df_pred.columns=["actual"]
df_pred = df_pred[WINDOW:]
df_pred["predicted"] = pred

fig,axes = plt.subplots(2,1,figsize=(14,8),dpi=400)

plt.subplot(2,1,1)
plt.title("Validation Results")
plt.plot(df_pred['predicted'][800:1000], label='Predicted',alpha=0.
 ↪8,linestyle=None)
plt.plot(df_pred['actual'][800:1000], label='Actual',alpha=0.8,linestyle=None)
plt.legend()
plt.subplot(2,1,2)
plt.title("Test Results")
plt.plot(df_pred['predicted'][1000:], label='Predicted',alpha=0.
 ↪8,linestyle=None)
plt.plot(df_pred['actual'][1000:], label='Actual',alpha=0.8,linestyle=None)
plt.legend()
```

[22]: <matplotlib.legend.Legend at 0x7f69bc6cf5b0>



Validation Results
Predicted
Actual
35
30
25
20
15
10
825
850
875
900
925
950
975
1000

Test Results
Predicted
Actual
35
30
25
20
15
10
5
1000
1100
1200
1300
1400