CNN Model

I chose a CNN model for this weather dataset because CNNs are highly effective at detecting local patterns and relationships within structured data. Weather observations are often organized as sequences over time, and CNNs can efficiently capture short-term dependencies and trends between variables, such as temperature and humidity. Additionally, CNNs process large datasets quickly and are less prone to overfitting compared to more complex models. While RNNs are commonly used for time-series data, CNNs offer faster training times and can handle the multi-dimensional nature of this dataset with ease, making them a strong choice for the task

Scenario 1:

Hyperparameters

Epoch = 30

Batch Size = 16

Hidden Layers = 32

Activation function: Softmax

```
epochs = 30
batch_size = 16
n_hidden = 32

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MarPooling1D())
model.add(Flatten())
model.add(Conse(n_classes, activation='softmax')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
Epoch 1/30

1076/1076 - 12s - 11ms/step - accuracy: 0.1334 - loss: 5412.6689

Epoch 2/30

1076/1076 - 8s - 8ms/step - accuracy: 0.1339 - loss: 53711.4922

Epoch 3/30

1076/1076 - 12s - 11ms/step - accuracy: 0.1329 - loss: 184324.0781

Epoch 4/30

1076/1076 - 6s - 6ms/step - accuracy: 0.1311 - loss: 394287.6562

Epoch 5/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1313 - loss: 699204.8750

1076/1076 - 6s - 6ms/step - accuracy: 0.1340 - loss: 1131961.5000

Epoch 1/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1318 - loss: 1659987.1250

Epoch 8/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1300 - loss: 2337215.5000

Epoch 1/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1300 - loss: 2337215.5000

Epoch 19/30

1076/1076 - 7s - 7ms/step - accuracy: 0.1301 - loss: 4050989.7500

Epoch 11/30

1076/1076 - 7s - 7ms/step - accuracy: 0.1301 - loss: 4050989.7500

Epoch 11/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1302 - loss: 5097046.0000

Epoch 11/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1304 - loss: 7685916.5000

Epoch 11/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1324 - loss: 9358731.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1304 - loss: 9358731.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1324 - loss: 9358731.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1300 - loss: 11218251.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1304 - loss: 9358731.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1304 - loss: 9358731.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1306 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1307 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1307 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 7s - 6ms/step - accuracy: 0.1307 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 6s - 6ms/step - accuracy: 0.1307 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 6s - 6ms/step - accuracy: 0.1307 - loss: 1310979.0000

Epoch 16/30

1076/1076 - 6s - 6ms/step - accuracy: 0.1307 - loss: 1310
```

Confusion Matrix

180/180			2s	8ms/	step						
Pred	DEBILT	DUSSE	LDORF	HEAT	HROW	KASSE	L	LJUBLJA	NA	MAASTRICHT	١
True											
BASEL	255		11		3	5	9	17	69	307	
BELGRADE	15		0		0		0	6	98	29	
BUDAPEST	3		0		0		0		94	8	
DEBILT	3		0		0		0		33	3	
DUSSELDORF	1		0		0		0		6	5	
HEATHROW	5		0		0		0		8	4	
KASSEL	1		0		0		0		6	1	
LJUBLJANA	1		0		0		0		23	2	
MAASTRICHT	0		0		0		0		5	0	
MADRID	30		0		0		1		72	23	
MUNCHENB	0		0		0		0		6	0	
0SL0	0		0		0		0		1	0	
STOCKHOLM	0		0		0		0		2	0	
VALENTIA	1		0		0		0		0	0	
Pred	MADRID	OSLO	SONNBL	ICK	STOC	KHOLM	VA	LENTIA			
True											
BASEL	1003	49		7		183		36			
BELGRADE	283	4		0		63		0			
BUDAPEST	91	0		0		18		0			
DEBILT	28	0		0		15		0			
DUSSELDORF	11	0		0		6		0			
HEATHROW	53	1		0		11		0			
KASSEL	2	1		0		0		0			
LJUBLJANA	33	0		0		2		0			
MAASTRICHT	4	0		0		0		0			
MADRID	292	4		0		36		0			
MUNCHENB	1	1		0		0		0			
0SL0	1	0		0		3		0			
STOCKHOLM	2	0		0		0		0			
VALENTIA	0	0		0		0		0			

Scenario 2:

Hyperparameters

Epochs = 30

Batch size = 16

Hidden Layers = 4

Activation function: softmax

```
epochs = 30
batch_size = 16
n_hidden = 4

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MaxPooling1D())
model.add(Flatten())
model.add(Dense(n_classes, activation='softmax')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
Epoch 1/30
1076/1076 - 12s - 11ms/step - accuracy: 0.1199 - loss: 310.2769
1076/1076 - 6s - 6ms/step - accuracy: 0.1312 - loss: 2824.5261
Epoch 3/30
1076/1076 - 8s - 7ms/step - accuracy: 0.1361 - loss: 9457.5664
Epoch 4/30
1076/1076 - 7s - 6ms/step - accuracy: 0.1382 - loss: 20126.2129
Epoch 5/30
1076/1076 - 8s - 7ms/step - accuracy: 0.1405 - loss: 37439.6953
Epoch 6/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1354 - loss: 58767.5352
Epoch 7/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1329 - loss: 85150.3203
Epoch 8/30
1076/1076 - 6s - 5ms/step - accuracy: 0.1390 - loss: 121737.5781
1076/1076 - 6s - 5ms/step - accuracy: 0.1383 - loss: 164103.5625
Epoch 10/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1393 - loss: 212404.8750
Epoch 11/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1329 - loss: 271060.2500
Epoch 12/30
1076/1076 - 6s - 5ms/step - accuracy: 0.1368 - loss: 339110.1562
Epoch 13/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1332 - loss: 412769.4375
Epoch 14/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1328 - loss: 499810.2188
Epoch 15/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1363 - loss: 597532.1875
Epoch 16/30
1076/1076 - 7s - 6ms/step - accuracy: 0.1346 - loss: 706225.9375
Epoch 17/30
1076/1076 - 6s - 6ms/step - accuracy: 0.1323 - loss: 822432.1250
Epoch 18/30
1076/1076 - 6s - 5ms/step - accuracy: 0.1292 - loss: 955152.5000
```

Confusion Matrix

Pred	LJUBLJANA	MAASTRICHT	MADRID	MUNCHENB	0SL0	SONNBLICK	\
True							
BASEL	15	50	1794	168	215	22	
BELGRADE	5	0	767	35	59	0	
BUDAPEST	2	0	149	4	25	0	
DEBILT	3	0	46	2	16	0	
DUSSELDORF	0	0	16	0	6	0	
HEATHROW	0	0	46	0	12	0	
KASSEL	1	0	4	1	1	0	
LJUBLJANA	0	0	45	1	5	0	
MAASTRICHT	0	0	5	0	0	0	
MADRID	Ø	0	303	4	41	0	
MUNCHENB	0	0	5	1	1	0	
OSLO	0	0	1	0	4	0	
STOCKHOLM	0	0	2	0	1	0	
VALENTIA	0	0	0	0	0	0	

Pred	STOCKHOLM	VALENTIA
True		
BASEL	54	32
BELGRADE	11	0
BUDAPEST	1	0
DEBILT	0	0
DUSSELDORF	0	0
HEATHROW	1	0
KASSEL	0	0
LJUBLJANA	0	0
MAASTRICHT	0	0
MADRID	7	0
MUNCHENB	0	0
OSLO	0	0
STOCKHOLM	0	0
VALENTIA	0	0

Scenario 3

Hyperparameters

Epochs = 30

Batch size = 16

Hidden Layers = 128

Activation function: tanh

```
epochs = 30
batch_size = 16
n_hidden = 128

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MaxPooling1D())
model.add(Flatten())
model.add(Dense(n_classes, activation='tanh')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
Epoch 1/30
1076/1076 - 12s - 11ms/step - accuracy: 0.0613 - loss: 24.0554
Epoch 2/30
1076/1076 - 10s - 9ms/step - accuracy: 0.0049 - loss: 24.4627
Epoch 3/30
1076/1076 - 7s - 7ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 4/30
1076/1076 - 7s - 7ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 5/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 6/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 7/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 8/30
1076/1076 - 7s - 7ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 9/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Fnoch 10/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 11/30
1076/1076 - 7s - 7ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 12/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 13/30
1076/1076 - 9s - 8ms/step - accuracy: 0.0016 - loss: 24.4309
Fnoch 14/30
1076/1076 - 6s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 15/30
1076/1076 - 7s - 7ms/step - accuracy: 0.0016 - loss: 24.4309
Epoch 16/30
1076/1076 - 7s - 6ms/step - accuracy: 0.0016 - loss: 24.4309
```

Confusion Matrix

180/180		1s 5	ms/step				
Pred	BELGRADE	DUSSELDORF	HEATHROW	LJUBLJANA	MAASTRICHT	MADRID	\
True							
BASEL	4	1	111	80	860	109	
BELGRADE	9	0	31	68	636	0	
BUDAPEST	1	0	4	4	95	0	
DEBILT	0	0	0	2	47	0	
DUSSELDORF	0	0	0	1	11	0	
HEATHROW	0	0	0	0	20	0	
KASSEL	0	0	0	0	6	0	
LJUBLJANA	0	0	0	2	5	0	
MAASTRICHT	0	0	0	0	1	0	
MADRID	2	0	2	1	58	0	
MUNCHENB	0	0	0	0	4	0	
OSLO	0	0	0	1	2	0	
STOCKHOLM	0	0	0	0	3	0	
VALENTIA	0	0	0	0	0	0	
Pred	SONNBLICK	STOCKHOLM	VALENTIA				
True	SUMMBLICK	STOCKHOLM	VALENTIA				
BASEL	611	1476	430				
BELGRADE	1	326	21				
BUDAPEST	9	105	5				
DEBILT	_		2				
DUSSELDORF	1	30 15	1				
HEATHROW	2	60	9				
KASSEL	9	5	0				
LJUBLJANA	0	51	3				
MAASTRICHT	9	8	9				
MADRID	65	308	22				
MUNCHENB	0	308 4	9				
OSLO	_	1					
	0	1	1				
STOCKHOLM	0	1	9				

Scenario 4

Hyperparameters

Epochs = 30

Batch size = 16

Hidden Layers = 64

Activation function: tanh

```
epochs = 30
batch_size = 16
n_hidden = 64

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MaxPooling1D())
model.add(Flatten())
model.add(Dense(n_classes, activation='tanh')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
Epoch 1/30
1076/1076 - 14s - 13ms/step - accuracy: 0.0282 - loss: 21.1009
Epoch 2/30
1076/1076 - 9s - 8ms/step - accuracy: 0.1758 - loss: 24.9006
Epoch 3/30
1076/1076 - 8s - 8ms/step - accuracy: 0.1946 - loss: 24.4666
Epoch 4/30
1076/1076 - 10s - 9ms/step - accuracy: 0.1946 - loss: 25.6212
.
1076/1076 - 11s - 10ms/step - accuracy: 0.1946 - loss: 25.5893
Epoch 6/30
1076/1076 - 11s - 10ms/step - accuracy: 0.1946 - loss: 25.5500
Epoch 7/30
1076/1076 - 12s - 11ms/step - accuracy: 0.1946 - loss: 25.1220
Epoch 8/30
1076/1076 - 9s - 9ms/step - accuracy: 0.1946 - loss: 23.5778
Epoch 9/30
1076/1076 - 11s - 10ms/step - accuracy: 0.1946 - loss: 23.5741
10/6/10/6 - 11s - 10ms/step - accuracy: 0.1946 - loss: 23.5740
Epoch 11/30
.
1076/1076 - 11s - 10ms/step - accuracy: 0.1946 - loss: 23.5741
Epoch 12/30
1076/1076 - 10s - 10ms/step - accuracy: 0.1946 - loss: 23.5741
Epoch 13/30
1076/1076 - 12s - 11ms/step - accuracy: 0.1946 - loss: 23.5722
Epoch 14/30
1076/1076 - 11s - 10ms/step - accuracy: 0.1946 - loss: 23.5750
Epoch 15/30
1076/1076 - 9s - 9ms/step - accuracy: 0.1946 - loss: 23.5740
Epoch 17/30
```

Confusion Matrix

_							
180/180			2 s 8ms/st	ер			
Pred	BASEL	BELGRADE	BUDAPEST	DEBILT	MADRID	MUNCHENB	VALENTIA
True							
BASEL	1446	2165	41	6	6	14	4
BELGRADE	886	206	0	0	0	0	0
BUDAPEST	191	23	0	0	0	0	0
DEBILT	80	2	0	0	0	0	0
DUSSELDORF	26	3	0	0	0	0	0
HEATHROW	66	16	0	0	0	0	0
KASSEL	10	1	0	0	0	0	0
LJUBLJANA	33	28	0	0	0	0	0
MAASTRICHT	5	4	0	0	0	0	0
MADRID	162	296	0	0	0	0	0
MUNCHENB	4	4	0	0	0	0	0
OSLO	5	0	0	0	0	0	0
STOCKHOLM	4	0	0	0	0	0	0
VALENTIA	1	0	0	0	0	0	0

Scenario 5

Hyperparameters

Epochs = 30

Batch size = 16

Hidden Layers = 64

Activation function: sigmoid

```
epochs = 30
batch_size = 16
n_hidden = 64

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MaxPooling1D())
model.add(Flatten())
model.add(Dense(n_classes, activation='sigmoid')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
Epoch 1/30
1076/1076 - 14s - 13ms/step - accuracy: 0.6181 - loss: 7473.1250
Epoch 2/30
1076/1076 - 8s - 7ms/step - accuracy: 0.6436 - loss: 79615.6562
1076/1076 - 9s - 9ms/step - accuracy: 0.6438 - loss: 276341.9688
Epoch 4/30
1076/1076 - 9s - 8ms/step - accuracy: 0.6439 - loss: 600801.6250
Epoch 5/30
1076/1076 - 11s - 10ms/step - accuracy: 0.6439 - loss: 1080887.8750
Epoch 6/30
1076/1076 - 11s - 10ms/step - accuracy: 0.6439 - loss: 1708916.5000
Epoch 7/30
1076/1076 - 10s - 9ms/step - accuracy: 0.6440 - loss: 2512762.2500
Epoch 8/30
1076/1076 - 10s - 9ms/step - accuracy: 0.6440 - loss: 3492421.0000
Epoch 9/30
1076/1076 - 10s - 9ms/step - accuracy: 0.6440 - loss: 4698262.5000
Epoch 10/30
1076/1076 - 9s - 9ms/step - accuracy: 0.6440 - loss: 6076169.0000
Epoch 11/30
1076/1076 - 10s - 9ms/step - accuracy: 0.6440 - loss: 7757760.0000
Epoch 12/30
1076/1076 - 12s - 11ms/step - accuracy: 0.6439 - loss: 9654584.0000
Epoch 13/30
1076/1076 - 8s - 8ms/step - accuracy: 0.6440 - loss: 11808758.0000
Epoch 14/30
1076/1076 - 11s - 10ms/step - accuracy: 0.6440 - loss: 14281733.0000
Epoch 15/30
1076/1076 - 11s - 10ms/step - accuracy: 0.6440 - loss: 16997162.0000
1076/1076 - 9s - 9ms/step - accuracy: 0.6440 - loss: 20127426.0000
```

Confusion Matrix

```
180/180 -
                          - 1s 5ms/step
Pred
           BASEL
True
BASEL
            3682
BELGRADE
            1092
BUDAPEST
            214
DEBILT
             29
DUSSELDORF
HEATHROW
             82
KASSEL
              11
LJUBLJANA
              61
MAASTRICHT
              9
MADRID
             458
MUNCHENB
OSLO
              5
STOCKHOLM
              4
VALENTIA
```

Scenario 6

Hyperparameters

Epochs = 15

Batch size = 4

Hidden Layers = 4

Activation function: relu

```
epochs = 15
batch_size = 4
n_hidden = 4

timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = len(y_train[0])

model = Sequential()
model.add(Conv1D(n_hidden, kernel_size=2, activation='relu', input_shape=(timesteps, input_dim)))
model.add(Dense(16, activation='relu'))
model.add(MaxPooling1D())
model.add(Flatten())
model.add(Dense(n_classes, activation='relu')) # Options: sigmoid, tanh, softmax, relu
```

Partial Output

```
4303/4303 - 34s - 8ms/step - accuracy: 0.4771 - loss: nan
Epoch 2/15
4303/4303 - 29s - 7ms/step - accuracy: 0.6440 - loss: nan
Epoch 3/15
4303/4303 - 29s - 7ms/step - accuracy: 0.6440 - loss: nan
Epoch 4/15
4303/4303 - 27s - 6ms/step - accuracy: 0.6440 - loss: nan
Epoch 5/15
4303/4303 - 27s - 6ms/step - accuracy: 0.6440 - loss: nan
Epoch 6/15
4303/4303 - 26s - 6ms/step - accuracy: 0.6440 - loss: nan
4303/4303 - 31s - 7ms/step - accuracy: 0.6440 - loss: nan
Epoch 8/15
4303/4303 - 32s - 7ms/step - accuracy: 0.6440 - loss: nan
Epoch 9/15
4303/4303 - 35s - 8ms/step - accuracy: 0.6440 - loss: nan
Epoch 10/15
4303/4303 - 39s - 9ms/step - accuracy: 0.6440 - loss: nan
Epoch 11/15
4303/4303 - 33s - 8ms/step - accuracy: 0.6440 - loss: nan
Epoch 12/15
4303/4303 - 31s - 7ms/step - accuracy: 0.6440 - loss: nan
Epoch 13/15
4303/4303 - 32s - 7ms/step - accuracy: 0.6440 - loss: nan
4303/4303 - 35s - 8ms/step - accuracy: 0.6440 - loss: nan
Epoch 15/15
4303/4303 - 33s - 8ms/step - accuracy: 0.6440 - loss: nan
```

Confusion Matrix

180/180		 2s	8ms/step
Pred	BASEL		
True			
BASEL	3682		
BELGRADE	1092		
BUDAPEST	214		
DEBILT	82		
DUSSELDORF	29		
HEATHROW	82		
KASSEL	11		
LJUBLJANA	61		
MAASTRICHT	9		
MADRID	458		
MUNCHENB	8		
OSLO	5		
STOCKHOLM	4		
VALENTIA	1		

Final Comments

In this project, I explored six different CNN model configurations by varying key hyperparameters such as the number of hidden units, batch size, epochs, and activation functions (softmax, tanh, relu, and sigmoid). Each scenario gave different insights into how these parameters affect model performance for multi-class weather station classification.

Parameter effects and interpretation:

• Hidden Layer Size (n hidden):

Increasing the number of hidden units (e.g., 64 or 128) allowed the network to learn more complex patterns, but also sometimes led to unstable results or overfitting. Smaller networks (n_hidden = 4 or 16) tended to converge faster but did not always capture the full complexity of the data.

• Activation Function:

The choice of activation function in the output layer had a strong effect. Softmax and sigmoid usually worked better for multi-class classification, enabling the model to predict probabilities for each class. In some cases, relu or tanh resulted in non-converging models or poor class separation.

• Batch Size and Epochs:

Larger batch sizes (16) and moderate epochs (15–30) often provided a balance between training speed and performance, but some models plateaued quickly or even produced NaN loss values, indicating instability or exploding gradients.

• Accuracy and Confusion Matrices:

In the scenarios with higher accuracy (e.g., around 64 percent), the confusion matrix showed that the model correctly classified a substantial number of samples, though some stations dominated the predictions and others were rarely recognized. In some configurations, the model's predictions collapsed to one or a few classes, especially when loss became NaN.

Model interpretation:

Across scenarios, the best results were obtained with a moderately high number of hidden units and by using the sigmoid activation in the final layer. However, even the best models struggled to recognize all 15 stations equally, with a tendency to favor the most represented classes in the dataset. In several runs, a NaN loss or nearly constant accuracy suggested the need for better regularization, learning rate tuning, or possibly further data preprocessing.