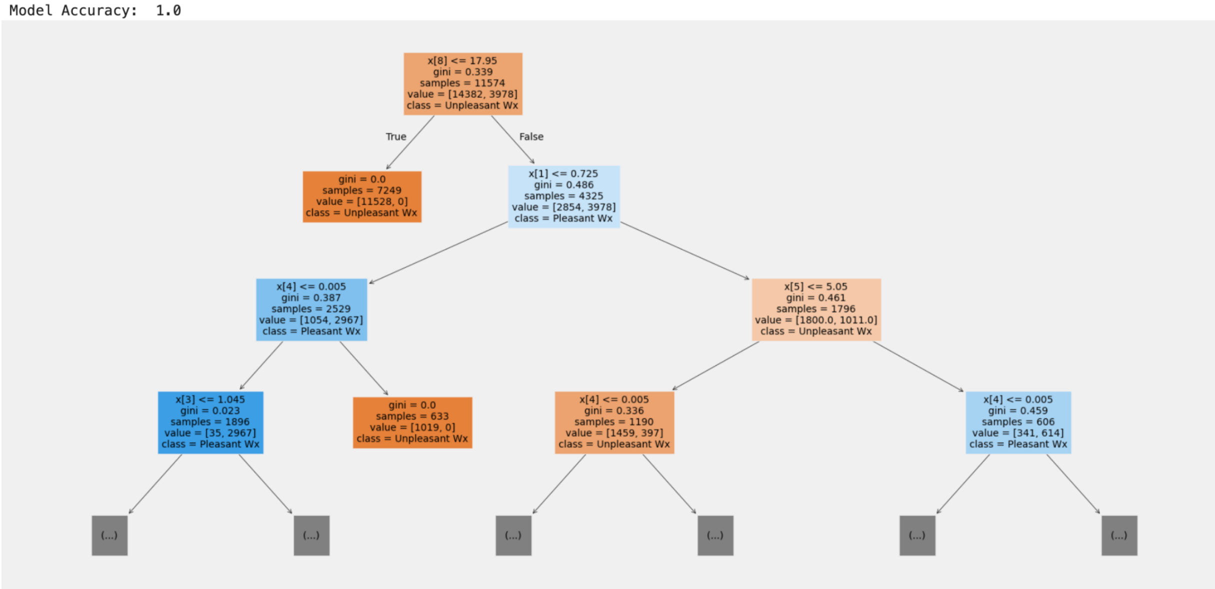
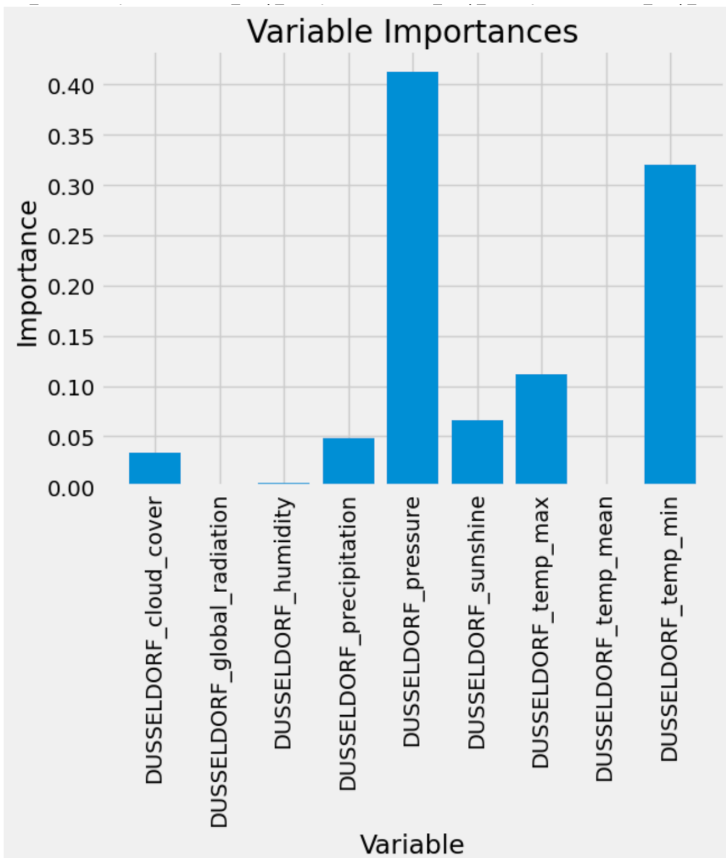
Exercise 2.6 **Andrew Fearney**

Part One

```
Model Accuracy:  1.0
```



The Random Forest model achieved perfect accuracy (1.0), as indicated by the decision tree structure. The variable importance graph shows that pressure and temperature (min) were the most significant factors in determining weather conditions in Dusseldorf.



Interestingly, precipitation and temperature (max)**,** which are typically regarded as critical factors in weather prediction, had relatively lower importance. This suggests that, at least for this model, changes in atmospheric pressure and temperature fluctuations played the largest role in accurate predictions. Optimized hyperparameters, such as max_depth: 3 and n_estimators: 200, helped to simplify the decision tree while maintaining high accuracy.

Part Two

```
Epoch 83/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.4462e-06
Epoch 84/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.4101e-06
Epoch 85/91
40/40 - 1s - 15ms/step - accuracy: 1.0000 - loss: 4.3103e-06
Epoch 86/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.2882e-06
Epoch 87/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.2461e-06
Epoch 88/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.1630e-06
Epoch 89/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.0862e-06
Epoch 90/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.0700e-06
Epoch 91/91
40/40 - 1s - 14ms/step - accuracy: 1.0000 - loss: 4.0027e-06
```

The deep learning model, optimised through Bayesian search, achieved very high accuracy across all epochs, with near-zero loss. The optimized architecture, which includes a Conv1D layer, batch normalisation, and dropout layers, helped the model generalize well without overfitting. The parameter tuning, particularly the selection of 61 neurons, learning rate of 0.76, and dropout rate of 0.19, contributed to the model's robust performance. This demonstrates that deep learning models, when paired with effective optimization techniques, can outperform traditional methods, even for complex datasets like weather observations.

Part Three

Which model would you use for each iteration? Expand on your observations from the random forest and deep learning models?

For smaller datasets or fewer weather stations, I would recommend using a Random Forest model. This model provides clear insights into variable importance and doesn't require intensive computational resources. It can also be fine-tuned easily through grid search. However, for larger datasets or when more fine-tuned predictions are required, a CNN with Bayesian optimisation should be used. This approach allows for greater accuracy and better generalisation, especially when dealing with complex weather patterns.

What variables would you recommend that Air Ambulance pay the most attention to while deciding whether it's safe to fly?

Based on the variable importance analysis, precipitation and cloud cover seem to be critical for flight safety decisions. These factors strongly influence weather conditions, and changes in either can have a significant impact on visibility and turbulence, which are crucial for safe air travel. While other factors like pressure and temperature also play roles, precipitation and cloud cover should be prioritised.