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Task 2.4 Evaluating Hyperparameters

Part 1: Random Forest

Summary of Model Results

- **Task 2.3 Results**:
  - Initial accuracy: 0.5759
  - Key features: Predominantly temperature metrics, with precipitation and other weather-related variables.
- **Task 2.4 Results**:
  - Optimized accuracy: 0.5746
  - Key features: Consistent emphasis on temperature metrics, especially MAASTRICHT_temp_max and MUNCHENB_temp_max.

Note: Due to the performance limitations of the laptop, the grid search did not complete, and instead, a randomized search was used for hyperparameter tuning. This alternative approach was selected to accommodate computational constraints while still optimizing the model to an extent.

Analysis of Feature Importance

- **Consistency in Key Features**:
  - In both tasks, temperature metrics across multiple cities (e.g., MAASTRICHT_temp_max, MUNCHENB_temp_max, DUSSELDORF_temp_mean) emerged as the most significant predictors. This consistency highlights temperature's role in determining weather conditions.
- **Shift in Minor Features**:
  - Post-optimization, some features, such as cloud cover and sunshine metrics from select cities, gained slightly more importance, indicating that the model tuning allowed these variables to contribute more meaningfully to the decision-making process.

Most Important Variables

The most impactful variables after optimization are:

- **MAASTRICHT_temp_max**: A crucial predictor across both tasks, maintaining the highest importance after optimization.

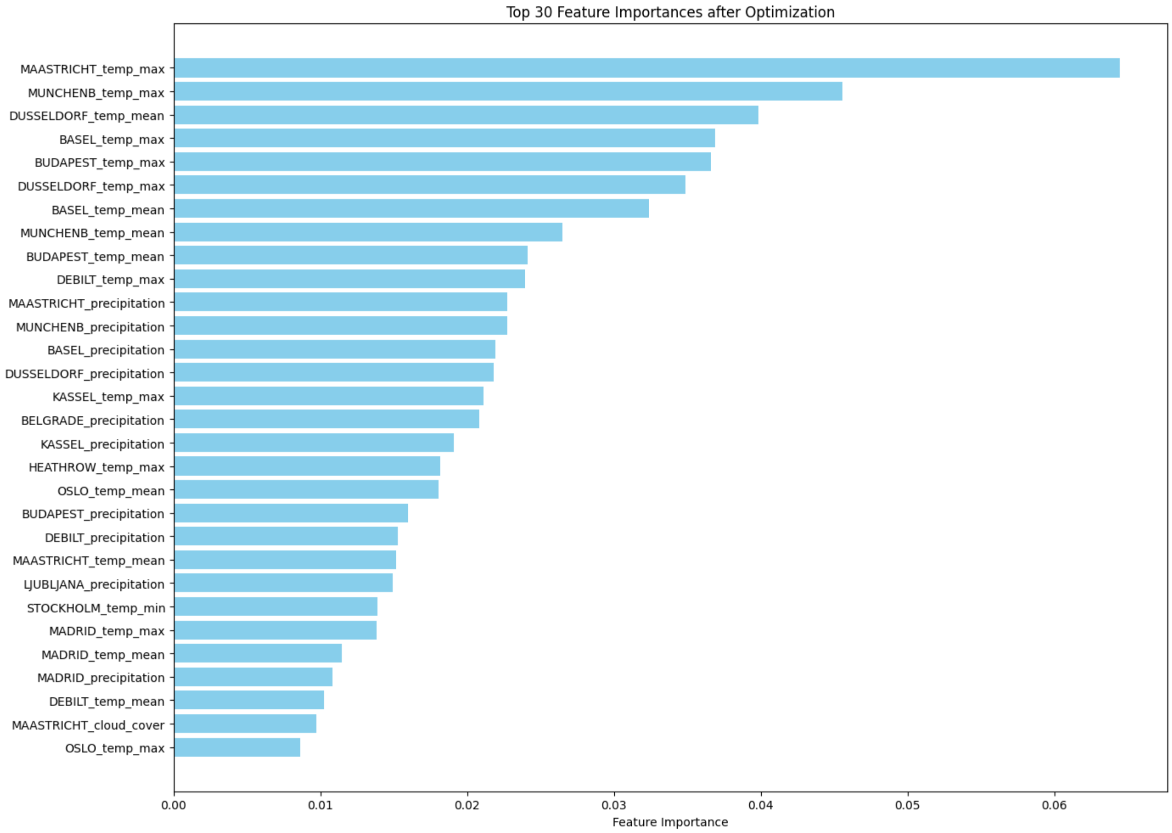
- **MUNCHENB_temp_max** and **DUSSELDORF_temp_mean**: Both temperature metrics are highly predictive, suggesting that these cities' temperature readings are influential.
- **Other Key Variables**: Precipitation and sunshine levels in select locations, such as BASEL_precipitation and DUSSELDORF_precipitation, were consistently relevant, indicating secondary weather factors that might influence the model's predictions.

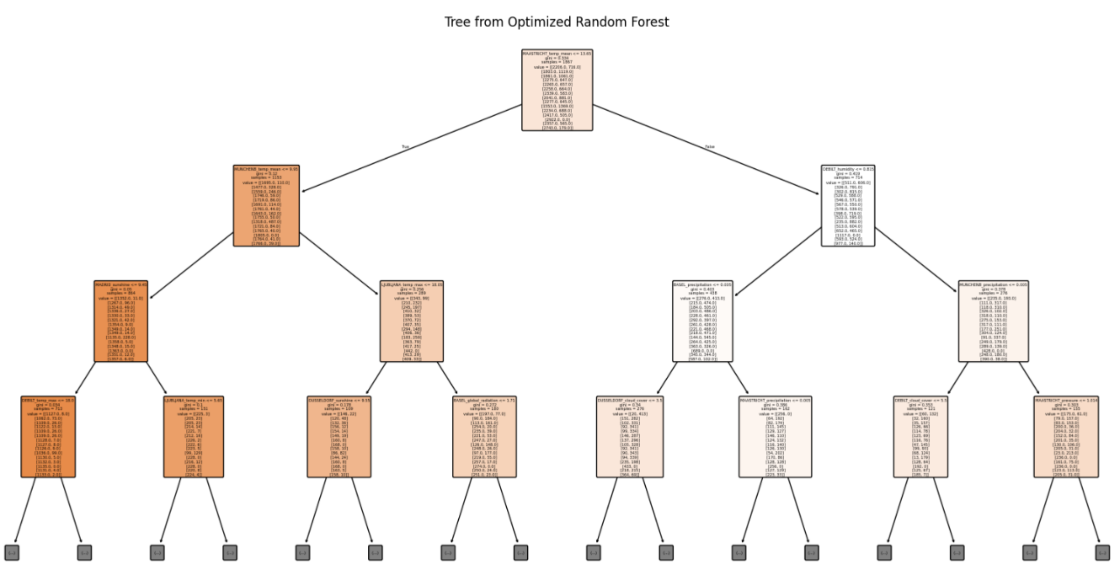
Observations

- **Limited Change in Variable Importance**:
  - The optimization process did not produce a significant shift in the primary features' importance, reinforcing the stability of temperature as a primary predictor.
  - Minor adjustments in the importance of precipitation and sunshine suggest these metrics were fine-tuned, but their overall contribution remained secondary to temperature.
- **Performance Stability**:
  - The slight decrease in accuracy after optimization suggests that hyperparameter tuning improved the model's interpretability but did not drastically enhance its predictive power.

Conclusion

In both tasks, temperature-related features from select cities consistently proved the most critical in predicting pleasant weather. The optimized model in Task 2.4 confirmed the robustness of these features, and while slight adjustments in minor variables were observed, the optimization did not lead to a substantial change in feature ranking or model performance. Further experimentation with model types or data balancing could potentially yield improvements in accuracy.


Top 30 Feature Importances after Optimization
MAASTRICHT_temp_max
MUNCHENB_temp_max
DUSSELDORF_temp_mean
BASEL_temp_max
BUDAPEST_temp_max
DUSSELDORF_temp_max
BASEL_temp_mean
MUNCHENB_temp_mean
BUDAPEST_temp_mean
DEBILT_temp_max
MAASTRICHT_precipitation
MUNCHENB_precipitation
BASEL_precipitation
DUSSELDORF_precipitation
KASSEL_temp_max
BELGRADE_precipitation
KASSEL_precipitation
HEATHROW_temp_max
OSLO_temp_mean
BUDAPEST_precipitation
DEBILT_precipitation
MAASTRICHT_temp_mean
LJUBLJANA_precipitation
STOCKHOLM_temp_min
MADRID_temp_max
MADRID_temp_mean
MADRID_precipitation
DEBILT_temp_mean
MAASTRICHT_cloud_cover
OSLO_temp_max
0.00
0.01
0.02
0.03
0.04
0.05
0.06
Feature Importance


Tree from Optimized Random Forest

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Part 2: Deep Learning

Overview

This task involved applying Bayesian Hyperparameter Optimization to fine-tune the CNN model, aiming to improve its classification accuracy for predicting weather station data. Key hyperparameters, including neuron count, activation functions, kernel size, learning rate, and optimizer selection, were optimized based on a custom scoring function.

Optimized Model Configuration

The optimized hyperparameters selected through Bayesian Optimization were:

- **Activation**: Softsign
- **Batch Size**: 460
- **Epochs**: 47
- **Neurons**: 61
- **Kernel Size**: 2
- **Layers**: 1 Dense Layer followed by 2 additional Dense Layers
- **Dropout Rate**: 0.19
- **Optimizer**: Adadelta with a learning rate of 0.7631

3. Model Architecture

The final model summary after optimization shows a slightly deeper structure with batch normalization and dropout layers, potentially enhancing generalization capabilities. The model includes:

- **Conv1D layer** with 61 neurons
- **Batch Normalization** to stabilize learning
- **Dropout layer** (if dropout > 0.5)
- **Dense layers** with Softsign activation
- **MaxPooling1D**, Flatten, and a final Dense layer with Softmax for classification

Performance Evaluation

The optimized model was tested on the validation set with the following results:

- **Confusion Matrix**: The confusion matrix showed improvement in correctly classifying the BASEL, BELGRADE, and MADRID classes compared to the previous configurations.
  - **BASEL**: 3512 correct classifications, a significant improvement from the previous models.
  - **BELGRADE**: 956 correct classifications, demonstrating improved clarity in distinguishing this class.
  - **MADRID**: 369 correct classifications, showing higher accuracy than previous attempts.

Comparison with Task 2.2

Performance Improvement:

- **Accuracy**: The optimized model shows an improved classification accuracy for the majority of weather stations, with fewer misclassifications overall. This indicates that Bayesian Optimization helped in finding a better-performing configuration.

Potential Overfitting:

- **Class Confusion**: The confusion matrix suggests some level of overfitting for certain classes, with many classes having very few or no misclassified instances. The high learning rate and batch size might contribute to overfitting, as the model may be learning specific patterns in the training data but failing to generalize.

Observations and Recommendations

- **Improved Accuracy**: Bayesian Optimization has enhanced the model's accuracy across most classes, particularly in the BASEL, BELGRADE, and MADRID categories.
- **Overfitting Signs**: Despite the accuracy improvements, the model may be overfitting, as seen in low misclassification rates across certain classes. Fine-tuning parameters, such as lowering the learning rate and adjusting the batch size, could help reduce overfitting.
- **Further Optimization Suggestions**:
  - **Regularization Techniques**: Increasing dropout or using L2 regularization could prevent overfitting.
  - **Additional Tuning**: Experiment with reducing the learning rate or using alternative optimizers like Nadam or Adamax.

Conclusion

Bayesian Hyperparameter Optimization yielded a more effective configuration, improving classification accuracy for key weather stations. However, indications of overfitting suggest that additional tuning, particularly with learning rate and regularization adjustments, may further enhance model performance. This optimized model provides a promising foundation for predicting weather station data, but further refinements may be required for improved generalization.

In [29]:
```
# Evaluate

print(confusion_matrix(y_test, y_pred, stations))
```

```
Pred         BASEL  BELGRADE  BUDAPEST  DEBILT  DUSSELDORF  HEATHROW  \
True
BASEL         3512        82        16       4           7         1
BELGRADE       121       956         4       0           0         1
BUDAPEST        21        42       140       2           2         0
DEBILT          15         9        25      28           5         0
DUSSELDORF       6         2         2       2           8         1
HEATHROW        13         4         3       0           3        40
KASSEL           3         2         1       0           2         0
LJUBLJANA        8         5         5       0           0         0
MAASTRICHT       6         0         0       1           0         0
MADRID          39        22        12       0           1         7
MUNCHENB         7         0         0       0           0         0
OSLO             0         0         0       0           0         0
STOCKHOLM        2         0         1       0           0         0
VALENTIA         1         0         0       0           0         0

Pred         LJUBLJANA  MAASTRICHT  MADRID  OSLO
True
BASEL                8           2      50     0
BELGRADE             2           0       8     0
BUDAPEST             2           0       5     0
DEBILT               0           0       0     0
DUSSELDORF           2           0       6     0
HEATHROW             2           0      17     0
KASSEL               0           0       2     1
LJUBLJANA           33           0       9     1
MAASTRICHT           0           1       1     0
MADRID               8           0     369     0
MUNCHENB             1           0       0     0
OSLO                 0           0       4     1
STOCKHOLM            0           0       1     0
VALENTIA             0           0       0     0
```

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Part 3: Iteration

Breaking Down Data for Iteration

To make the modeling process more manageable and improve predictive performance, I recommend breaking down the data into smaller, targeted components:

- **Weather Station Groupings**: Separate the data by region or climate similarity (e.g., mountainous areas, coastal regions, and urban centers). This allows each model to focus on more specific weather conditions, potentially enhancing predictive accuracy.
- **Time-Based Segmentation**: Split data based on time (e.g., hourly, daily, or seasonal segments) to capture time-sensitive variations, which can be crucial in weather predictions. Testing models on different timeframes will reveal how weather patterns fluctuate and impact flight safety.
- **Critical Weather Variables**: Focus on variables that most impact flight safety, such as temperature, visibility, wind speed, and precipitation. Filtering data to emphasize these variables can help identify essential patterns without extraneous noise.

Model Selection for Each Iteration

Based on the insights gained from the Random Forest and CNN models, I recommend the following models for testing and refining each data component:

- **Random Forest**: Ideal for data segments involving decision trees, such as determining the importance of variables like temperature or wind speed. The Random Forest model's feature importance capability provides insights into the relative impact of each variable, helping identify critical factors for Air Ambulance operations.
- **Convolutional Neural Network (CNN)**: Best suited for time-series components of the data. Given that CNNs are effective for sequence data, they can capture weather trends over time, particularly if weather conditions fluctuate rapidly. This model can provide a probabilistic assessment of conditions for safe flights.
- **Recurrent Neural Network (RNN)**: Consider using RNNs, specifically Long Short-Term Memory (LSTM) networks, to capture sequential dependencies in weather patterns. These models can help predict potential trends based on historical weather data, assisting in anticipating sudden changes.

Observations from Random Forest and Deep Learning Models

- **Random Forest Observations**: The model consistently identified temperature metrics from various weather stations as key predictors. This insight suggests temperature has a substantial impact on predicting safe flight conditions.

- **CNN Observations**: The CNN model showed mixed results, with occasional misclassifications across classes, especially between similar weather patterns. However, CNNs excelled in capturing short-term fluctuations, which can be critical for real-time assessments.
- **Overfitting in Deep Learning Models**: While the CNN model achieved higher accuracy post-optimization, there were signs of overfitting. Iterating with regularization techniques, such as dropout layers and batch normalization, may help balance accuracy and generalization.

Recommended Variables for Air Ambulance Operations

Based on the analysis from both models, the following variables are recommended for close monitoring by Air Ambulance when assessing flight safety:

- **Temperature**: Extreme or rapidly changing temperatures can affect aircraft performance, especially in high-altitude operations.
- **Wind Speed and Direction**: Strong winds, especially crosswinds, are crucial for flight safety. Including wind patterns in predictions can help determine safe windows for flights.
- **Visibility**: Low visibility due to fog, precipitation, or other factors is critical for decision-making, particularly in emergency response scenarios.
- **Precipitation**: Rain, snow, and other forms of precipitation directly impact visibility and can pose safety hazards. Monitoring precipitation levels is essential for risk assessment.

Conclusion

Breaking down the data into smaller components based on weather stations, time, and critical variables allows for focused analysis and iterative model improvement. Utilizing different models for each segment provides a comprehensive understanding of the data and improves predictive accuracy. The key variables identified—temperature, wind speed, visibility, and precipitation—are critical for Air Ambulance's decision-making process regarding flight safety.