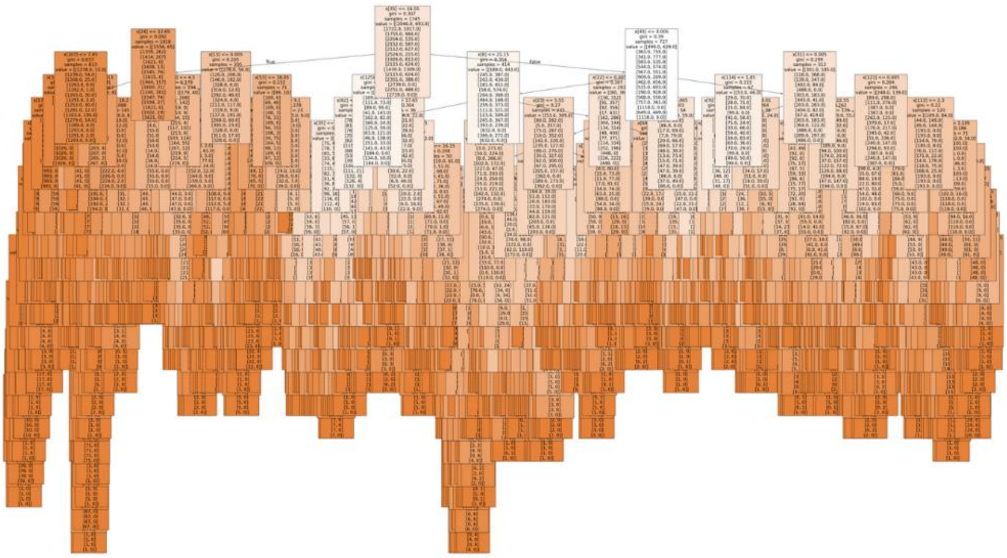
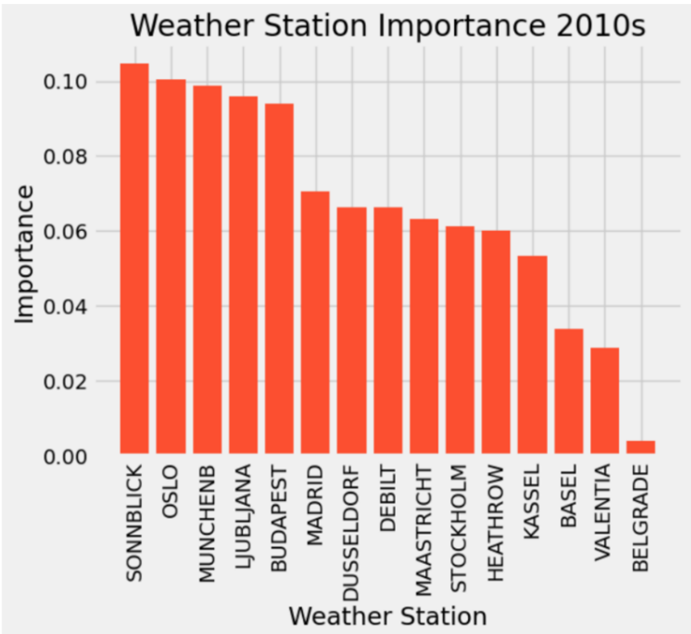
Part 1 – Random Forest Model

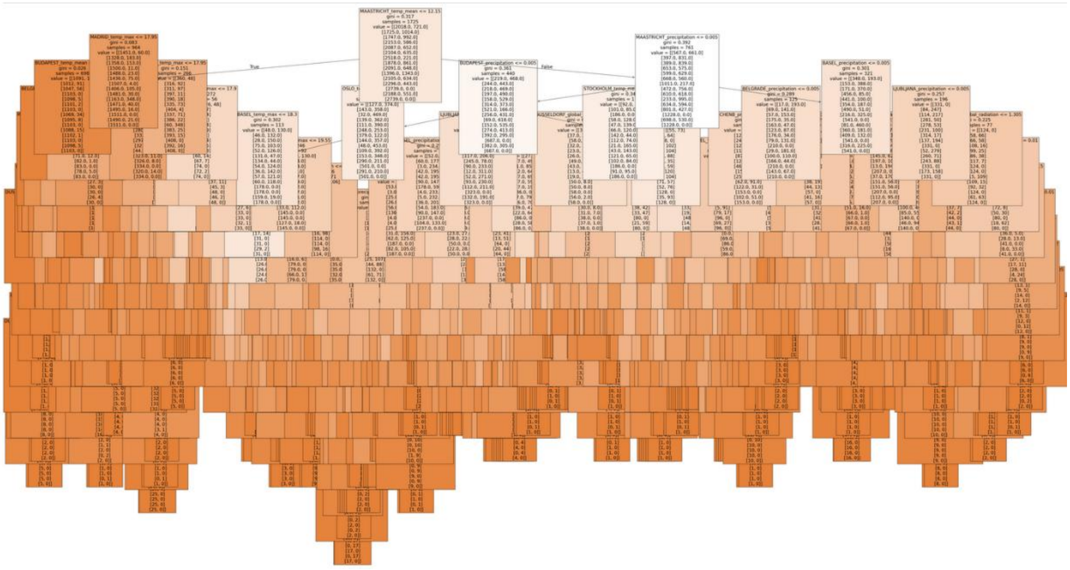
Data Subset	Accuracy Before Optimization	Accuracy After Optimization
All Weather Stations (2010-2019)	57.6%	66.5%
Oslo (All Years)	100%	100%

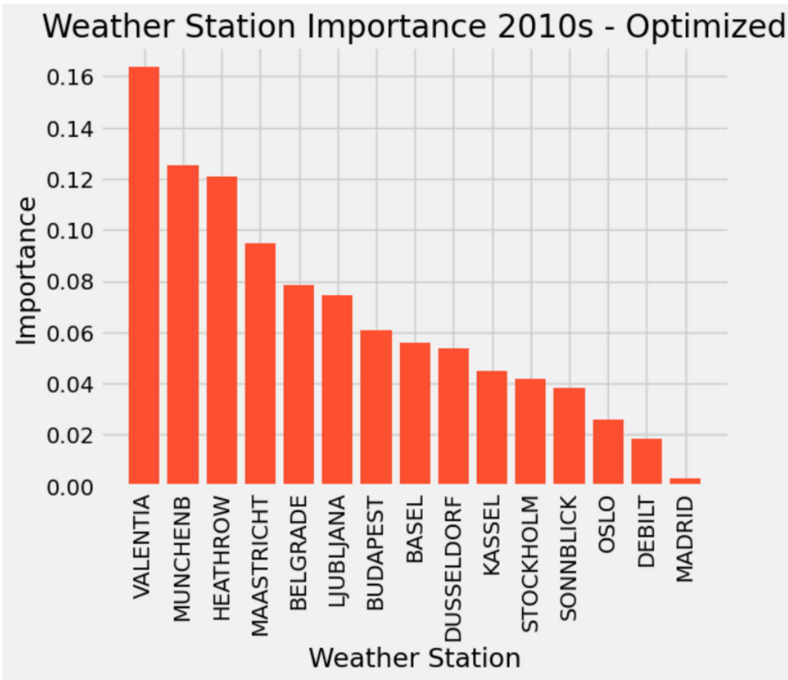
All Weather Stations Before Optimization





All Weather Stations After Optimization





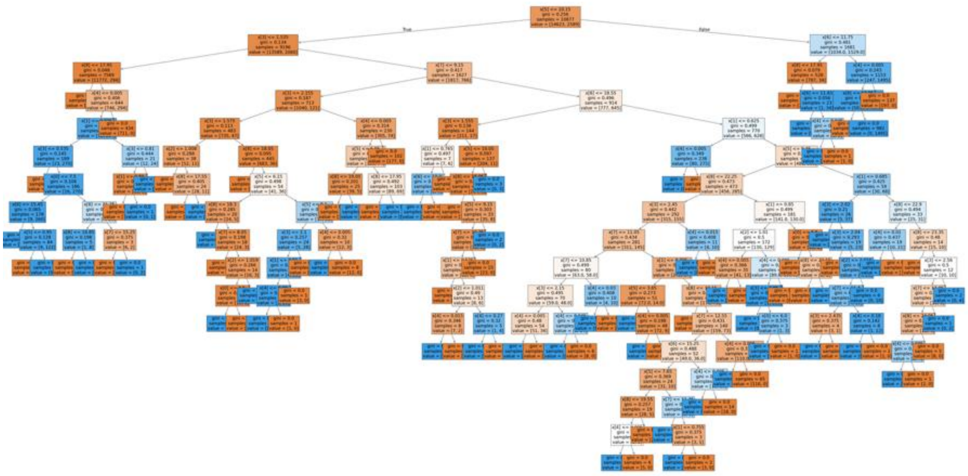
The model accuracy improved of +8.9% after the optimization. The decision trees from both models are complex to interpret, but while the unoptimized tree is deeper, with more layers and splits, the optimized version is simpler, less deep, more balanced, and has fewer splits, helping to prevent overfitting and improve generalization by focusing on the most impactful features and splits.

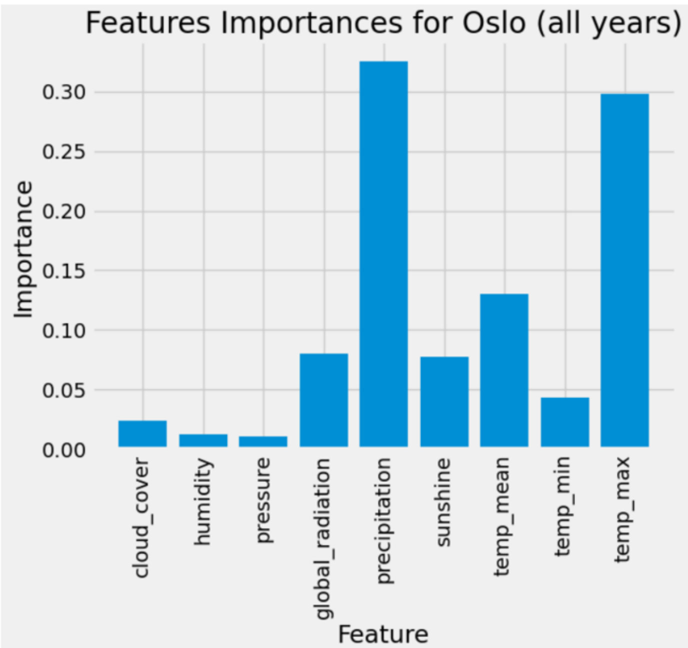
Some notable differences in the bar charts are:

• Sonnblick is no longer the most important station after optimization. München remains an important station after optimization, and Oslo also decreases in importance.

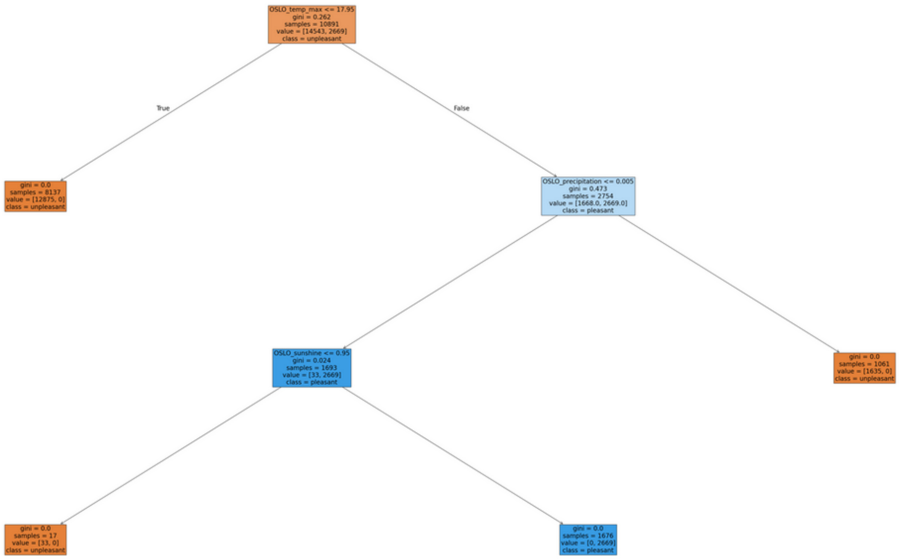
• The optimized chart reflects a rebalancing of weather station importance, giving more weight to dominant stations like Valentia, München, and Heathrow, while further reducing the relevance of lower-ranked stations.

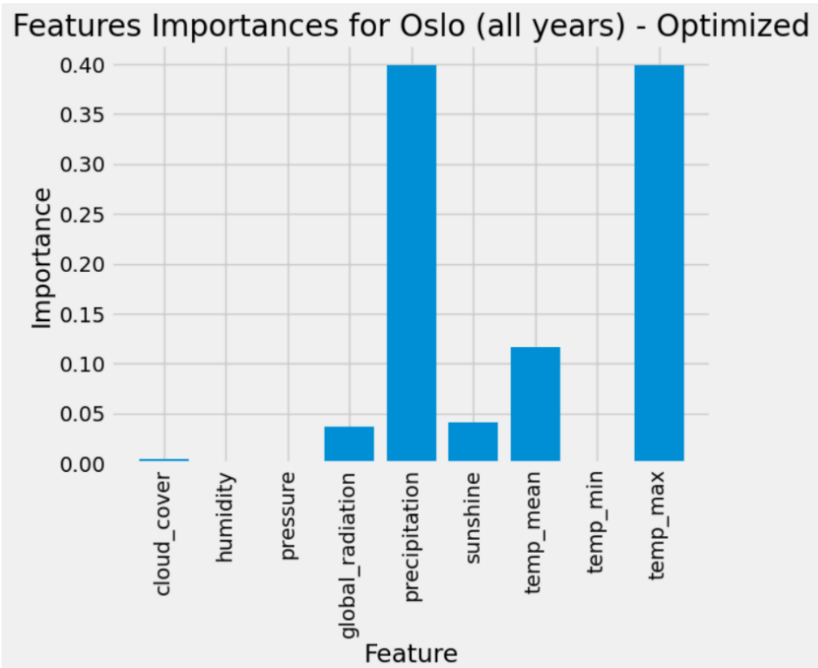
Oslo Before Optimization





Oslo After Optimization





After optimizing the hyperparameters for Oslo, the accuracy maintains stable at 100%. Notable differences are observed in the decision trees: the optimized version of the model has a more straightforward and concise tree structure, likely leading to better generalization, easier interpretation, and improved performance, while the unoptimized version is more complex and prone to overfitting. In addition, while the weight of the most significant features (temp_max and precipitation) remain largely unchanged, the least important ones now carry even less weight than before, indicating the optimized model is likely more efficient and focused on the most relevant factors for predicting weather at Oslo.

Part 2 – Deep Learning – CNN Model

Accuracy Before Optimization: 12.3%

Accuracy After Optimization: 92.2%

Parameter	Before Optimization	After Optimization
Neurons/n_hidden	256	61
epochs	30	47
Batch_size	32	460
Learning_rate	-	0.763
Kernel	2	2
activation	relu	softsign
optimizer	Adam	Adadelta
Layers 1	-	1
Layers 2	-	2
normalization	-	0.771
dropout	-	0.730
Dropout_rate	-	0.191

Pred	BASEL	BELGRADE	BUDAPEST	DEBILT	DUSSELDORF	HEATHROW	KASSEL	\
True								
BASEL	3572	83	8	3	1	1	0	
BELGRADE	158	931	0	0	0	0	0	
BUDAPEST	27	52	132	2	0	0	0	
DEBILT	16	7	16	42	1	0	0	
DUSSELDORF	8	2	6	1	7	2	0	
HEATHROW	13	4	3	1	4	49	0	
KASSEL	2	2	1	0	1	1	1	
LJUBLJANA	11	4	4	0	0	3	0	
MAASTRICHT	6	0	1	0	0	0	0	
MADRID	62	24	12	1	2	6	1	
MUNCHENB	7	1	0	0	0	0	0	
OSLO	1	0	0	0	1	0	0	
STOCKHOLM	2	0	1	0	0	0	0	
VALENTIA	1	0	0	0	0	0	0	

Pred	LJUBLJANA	MAASTRICHT	MADRID	OSLO	STOCKHOLM
True					
BASEL	2	1	11	0	0
BELGRADE	0	0	3	0	0
BUDAPEST	1	0	0	0	0
DEBILT	0	0	0	0	0
DUSSELDORF	0	0	3	0	0
HEATHROW	1	0	7	0	0
KASSEL	2	1	0	0	0
LJUBLJANA	35	0	3	1	0
MAASTRICHT	0	1	1	0	0
MADRID	3	1	346	0	0
MUNCHENB	0	0	0	0	0
OSLO	0	0	0	3	0
STOCKHOLM	0	0	0	0	1
VALENTIA	0	0	0	0	0

After optimizing the model, its accuracy increases dramatically by 79.9%, rising from 12.3% to 92.2%. This improvement is largely driven by key hyperparameter adjustments. The optimizer switches from Adam to Adadelta, the learning rate is fine-tuned to 0.763, and the batch size increases from 32 to 460. Additionally, the number of neurons in the hidden layers is reduced from 256 to 61, and the activation function changes from “relu” to “softsign.” New layers and kernels are introduced, with dropout regularization and normalization added to enhance performance.

Part 3 – Iteration

For the purpose of optimizing weather predictions for the Air Ambulance company, I recommend breaking down the dataset into smaller, more manageable components by location, time interval, or weather feature. For location, the data should be segmented by individual weather station, as we did for the random forest optimization, or by groups of weather stations with similar weather patterns (for example, continental versus coastal stations). This allows the model to focus on local weather dynamics in each area. Breaking the dataset into different time intervals, such as seasons, months, or years, could help capture seasonal changes and trends. Additionally, grouping data by specific weather metrics, such as temperature, precipitation, and sunshine, could be useful to test how each factor contributes to flight safety predictions.

When it comes to model selection, both models have their strengths and weaknesses. An optimized random forest offers transparency and interpretability, as it relies on decision trees based on feature importance, making predictions easier to explain. It requires fewer hyperparameters to tune compared to deep learning models and generally avoids overfitting by averaging results across multiple trees, leading to more generalizable predictions. However, it has limitations in capturing complex, non-linear relationships and may struggle to generalize to time frames outside the training data. It can also become computationally expensive with large datasets.

On the other hand, an optimized convolutional neural network (CNN) excels at detecting intricate spatial or temporal patterns, making it ideal for large and complex datasets. It scales well and can learn directly from raw data, reducing the need for feature engineering. However, it lacks transparency, making it harder to interpret, and it demands significant computational resources and extensive hyperparameter tuning, increasing the risk of overfitting if not carefully optimized. For all these reasons, I believe the optimized random forest should be used as a starting point for weather predictions, especially when breaking down the data by individual weather stations, where the model can reach up to 100 percent accuracy. The optimized CNN can then be introduced to explore more complex relationships and identify temporal patterns.

In terms of key weather variables critical to flight safety, the optimized random forest confirmed the importance of temperature, particularly maximum temperature, and precipitation as the main factors influencing predictions. Therefore, I suggest that Air Ambulance prioritize these variables in future analyses.