Weather Conditions and Climate Change with ClimateWins

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Introduction and Key Objectives

As climate change advances, weather patterns around the world are becoming increasingly unpredictable. This shift has resulted in a surge of extreme weather events, which pose growing risks to the safety of communities.

ClimateWins, a nonprofit organization, is dedicated to exploring innovative tools for predicting and categorizing weather in mainland Europe. By analyzing historical data, the goal is to develop a machine learning model that can forecast future weather trends, helping communities better prepare for these extremes.

The key objectives of ClimateWins include:

- Finding new patterns in weather changes over the last 60 years.
- Identifying weather patterns outside the regional norm in Europe.
- Determining whether unusual weather patterns are increasing.
- Generating possibilities for future weather conditions over the next 25 to 50 years based on current trends.
- Determining the safest places for people to live in Europe within the next 25 to 50 years.

Necessary Data

Satellite and Radar Imagery: To provide a visual context of changing weather patterns, enabling deep learning models like CNNs to identify significant trends and patterns.

Real-time Weather Station Data: To provide immediate updates to models, improving the accuracy of weather forecasts.

Extreme Weather Data: To provide records of severe weather events across Europe: storms, excessive heat, and extreme cold.

Dangerous Weather Classifications: To identify and classify hazardous weather conditions and helping to define what constitutes dangerous weather.

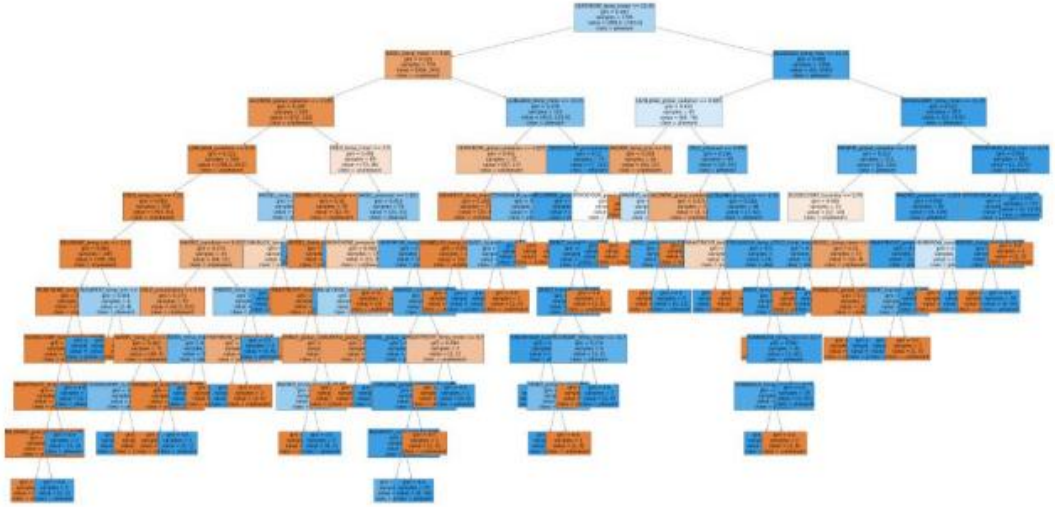
Overview of Machine Learning Models

Random Forest Model:

The data is classified using multiple decision tree models, where each tree applies true/false decisions to classify data points. Each tree is trained on a random sample of the data, and the results are averaged to generate the final prediction.

General Adversarial Network (GAN):

A GAN (Generative Adversarial Network) consists of two networks: a generator that creates synthetic data and a discriminator that distinguishes real from fake data. They improve through competition, making the generated data more realistic.



Correct Prediction - class: Shine - predicted: Shine

Correct Prediction - class: Sunrise - predicted: Sunrise

Overview of Machine Learning Models (cont.)

Deep Learning with CNNs:

Convolutional Neural Networks (CNNs) were used to classify weather conditions using radar and satellite imagery.
CNNs allowed for the analysis of complex spatial patterns in weather images.

Layer (type)	Output Shape	Param #
conv1d_75 (Conv1D)	(None, 14, 61)	1,159
batch_normalization_35 (BatchNormalization)	(None, 14, 61)	244
dense_410 (Dense)	(None, 14, 61)	3,782
dropout_35 (Dropout)	(None, 14, 61)	0
dense_411 (Dense)	(None, 14, 61)	3,782
dense_412 (Dense)	(None, 14, 61)	3,782
max_pooling1d_75 (MaxPooling1D)	(None, 7, 61)	0
flatten_75 (Flatten)	(None, 427)	0
dense_413 (Dense)	(None, 15)	6,420

```
38/38 - 1s - 38ms/step - accuracy: 0.9240 - loss: 0.2204
```

Pred / True	BASEL	BELGRADE	BUDAPEST	DEBILT	DUSSELDORF	HEATHROW	KASSEL
BASEL	3522	67	12	5	2	2	0
BELGRADE	116	993	1	1	0	0	0
BUDAPEST	25	36	134	1	0	0	0
DEBILT	7	8	8	59	1	0	0
DUSSELDORF	5	1	3	16	8	5	0
HEATHROW	16	5	2	3	4	61	0
KASSEL	1	6	3	0	1	0	3
LJUBLJANA	7	5	2	1	0	2	2
MAASTRICHT	3	0	0	0	0	0	0
MADRID	13	19	12	2	1	22	0
MUNCHENB	6	1	0	0	0	0	1
OSLO	0	0	0	1	0	0	0
STOCKHOLM	1	0	0	0	0	2	0
VALENTIA	1	0	0	0	0	1	0

Pred / True	LJUBLJANA	MAASTRICHT	MADRID	OSLO	STOCKHOLM
BASEL	3	1	64	0	0
BELGRADE	0	0	0	0	0
BUDAPEST	0	0	1	0	0
DEBILT	0	0	0	0	0
DUSSELDORF	0	0	0	0	0
HEATHROW	0	0	0	0	0
KASSEL	2	0	0	0	0
LJUBLJANA	30	0	0	0	0
MAASTRICHT	0	0	2	0	0
MADRID	7	0	375	0	0
MUNCHENB	0	0	1	0	0
OSLO	1	0	1	1	0
STOCKHOLM	0	0	0	0	1
VALENTIA	0	0	0	0	0

Thought Experiment #1: Classification of Unusual Weather

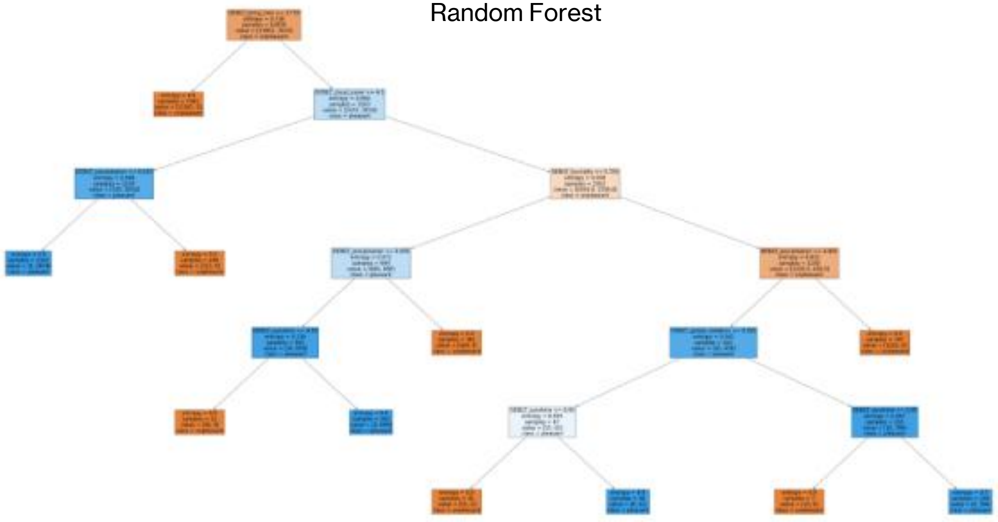
Hypothesis: A random forest model can detect unusual weather trends by analyzing historical data and station records.

Approach:

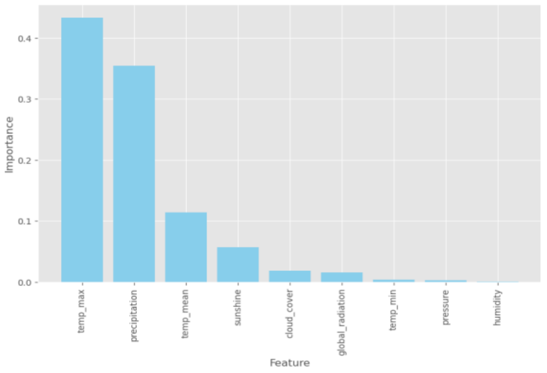
- Utilized the RandomForestClassifier to assess key variables like temperature and precipitation from various European weather stations.
- Used RandomizedSearchCV to optimize hyperparameters such as **n_estimators**, **max_depth**, and **min_samples_split**, improving model performance and accuracy.
- **Model Used:** RandomForestClassifier with optimized hyperparameters for improved prediction.

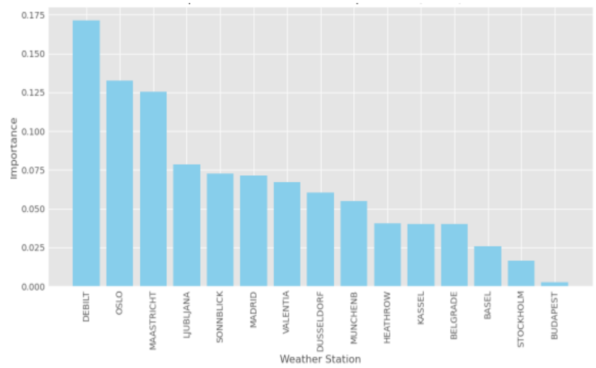
Result:

- Accuracy: Improved from 99.6% to 100% after hyperparameter optimization.
- This model effectively pinpointed regions showing deviations from historical trends, detecting the rising anomalies such as changes in precipitation and temperature extremes.



Random Forest





Thought Experiment #2: Deep Learning for Weather using Images

Hypothesis: CNNs can enhance the interpretation of radar and satellite imagery leading to more accurate weather trend predictions.
Approach:
- Developed a CNN model to classify radar images of various weather conditions (e.g., cloudy, rainy, sunny).
- Applied the Bayesian optimization to fine-tune hyperparameters such as the number of neurons, batch size, and learning rate to improve accuracy.
- **Model Used:** CNN with Bayesian optimization.

Results:
- **Initial Accuracy:** The unoptimized CNN achieved about 47.83% accuracy.
- **Optimized Model Accuracy:** After readjusting hyperparameters, accuracy improved drastically to 92.4%.
- **Confusion Matrix:** Displayed the model's ability to distinguish between weather conditions like 'shine' and 'sunrise,' with optimization reducing classification errors.
- The model demonstrated strong potential for analyzing complex visual data, making it valuable for predicting weather patterns and trends.

CNN before Optimization

```
1722/1722 - 10s - 6ms/step - accuracy: 0.4783 - loss: 27.1353
```

Pred	BASEL	BELGRADE	BUDAPEST	DUSSELDORF	KASSEL	MAASTRICHT \
True						
BASEL	2038	890	335	22	18	368
BELGRADE	484	614	0	0	0	13
BUDAPEST	85	112	0	0	0	0
DEBILT	38	45	0	0	0	0
DUSSELDORF	15	23	0	0	0	0
HEATHROW	46	44	0	0	0	1
KASSEL	7	9	0	0	0	0
LJUBLJANA	20	29	0	0	0	0
MAASTRICHT	2	3	0	0	0	0
MADRID	246	170	2	1	0	32
MUNCHENB	0	9	0	0	0	0
OSLO	0	4	0	0	0	0
STOCKHOLM	0	4	0	0	0	0
VALENTIA	0	2	0	0	0	0

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

CNN after Optimization

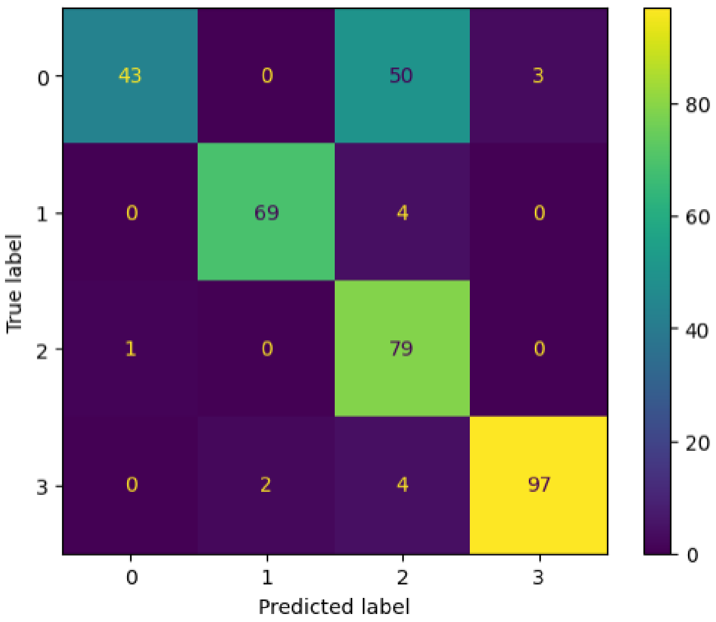
```
38/38 - 1s - 38ms/step - accuracy: 0.9240 - loss: 0.2204
```

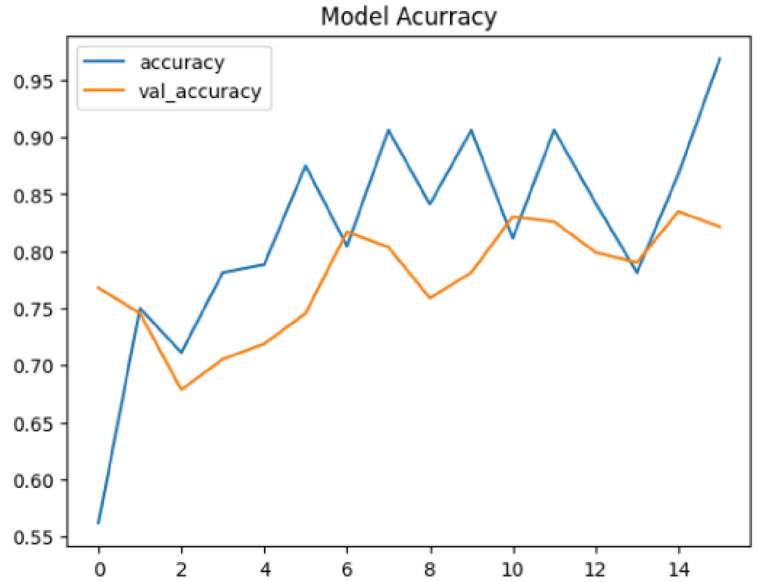
Pred	BASEL	BELGRADE	BUDAPEST	DEBILT	DUSSELDORF	HEATHROW	KASSEL \
True							
BASEL	3522	67	12	5	2	2	0
BELGRADE	116	993	1	1	0	0	0
BUDAPEST	25	36	134	1	0	0	0
DEBILT	7	8	8	59	1	0	0
DUSSELDORF	5	1	3	16	8	5	0
HEATHROW	16	5	2	3	4	61	0
KASSEL	1	6	3	0	1	0	3
LJUBLJANA	7	5	2	1	0	2	2
MAASTRICHT	3	0	0	0	0	0	0
MADRID	13	19	12	2	1	22	0
MUNCHENB	6	1	0	0	0	0	1
OSLO	0	0	0	1	0	0	0
STOCKHOLM	1	0	0	0	0	2	0
VALENTIA	1	0	0	0	0	1	0

Pred	LJUBLJANA	MAASTRICHT	MADRID	OSLO	STOCKHOLM
True					
BASEL	3	1	64	0	0
BELGRADE	0	0	0	0	0
BUDAPEST	0	0	1	0	0
DEBILT	0	0	0	0	0
DUSSELDORF	0	0	0	0	0
HEATHROW	0	0	0	0	0
KASSEL	2	0	0	0	0
LJUBLJANA	30	0	0	0	0
MAASTRICHT	0	0	2	0	0
MADRID	7	0	375	0	0
MUNCHENB	0	0	1	0	0
OSLO	1	0	1	1	0
STOCKHOLM	0	0	0	0	1
VALENTIA	0	0	0	0	0

Thought Experiment # 2: CNN Model Performance

```
Accuracy: 0.96875, Val_Accuracy: 0.8214285969734192
Loss: 0.026281258091330528, Val_Loss: 0.0785900354385376
```





Confusion Matrix:

Illustrates the model's performance in classifying weather types. While most predictions are correct, some categories are occasionally misclassified.

Model Accuracy:

Monitors accuracy across epochs. Higher values reflect better performance, while fluctuations indicate changes in model stability.

Model Loss:

Shows training and validation loss. Lower loss indicates a better fit, while spikes highlight areas that need improvement.

Thought Experiment #3: Synthetic Weather Projections using GANs to Improve Predictions

Hypothesis: GANs can generate realistic weather scenarios based on current trends, offering a range of possible future outcomes.

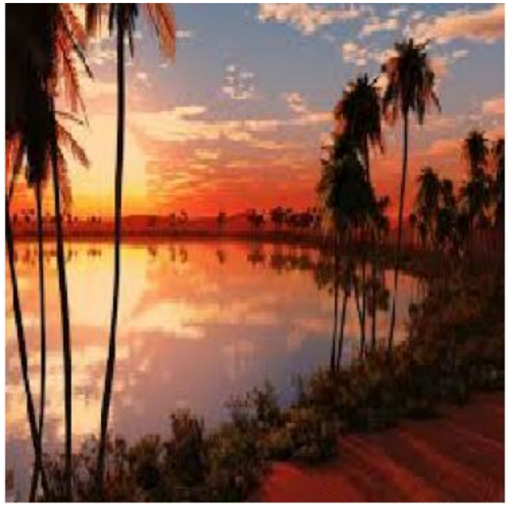
Approach:

- Leverage GANs to simulate diverse weather patterns and scenarios, such as temperature fluctuations or changes in precipitation over time.
- Generate synthetic weather maps to explore long-term projections (e.g., 25 to 50 years).

Results:

- A model that visualizes potential future climate conditions, enabling stakeholders to better prepare and plan for extreme weather events.

Correct Prediction - class: Sunrise - predicted: Sunrise



Incorrect Prediction - class: Cloudy - predicted: Shine

Recommendations & Next Steps

1. Utilize Random Forest models for quick analysis of feature significance and to pinpoint key indicators of unusual weather patterns.
2. Deploy CNNs to process satellite data and weather imagery, enhancing real-time weather classification accuracy.
3. Focus on developing GANs to simulate long-term climate scenarios, supporting ClimateWins in preparing for potential future weather conditions.
4. Further enhance and improve the Bayesian Optimization of CNN.
5. Validate model predictions using real-time data.
6. Prepare and gather additional information and data.

THANK YOU!

Questions:
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GitHub