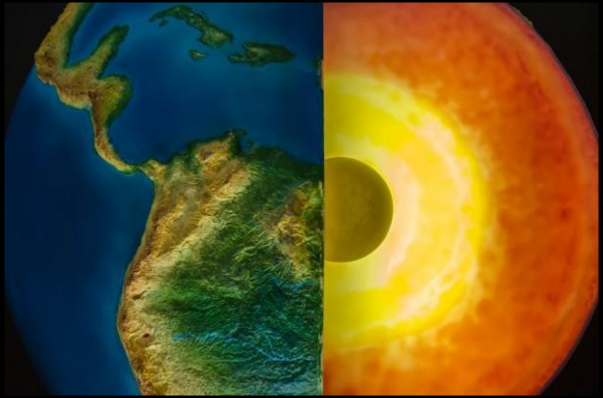
Predicting Weather Variations For ClimateWins



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Project Objectives

- Identify weather patterns outside the regional norm in Europe.
- Determine if unusual weather patterns are increasing.
- Generate possibilities for future weather conditions over the next 25 to 50 years based on current trends.
- Determine the safest places for people to live in Europe over the next 25 to 50 years.

Overview of Thought Experiments

1. **Detecting Out-of-Pattern Weather Events:**

   Use Random Forest to identify weather conditions that deviate from historical norms. This could help predict increasing weather anomalies like sudden heatwaves or unexpected storms.

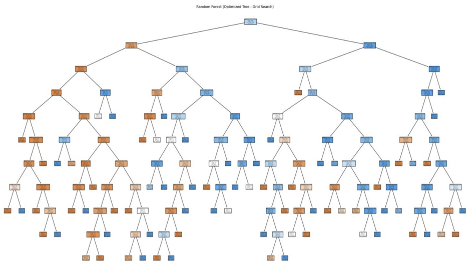
2. **Climate Trend Projection:**

   Apply CNNs to analyze satellite images and radar data to identify long-term trends, like temperature rise or shifting rainfall patterns. These insights would help ClimateWins forecast future climate changes over decades.

3. **Geographic Safety Index:**

   Use GANs to generate synthetic future weather scenarios and create a safety index for different European regions. This index would project areas likely to remain safe for living based on future climate risks.

Machine Learning Approaches



```python
# Evaluating the model

y_pred = np.argmax(final_model.predict(X_test), axis=1)
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
180/180 ━━━━━━━━━━━━━━━━━━━━ 0s 369us/step
Confusion Matrix:
 [[3481  109   13   13   10   14    4    3    1   33    1    0    0    0]
 [ 143  914    6    3    2    6    2    3    0   11    0    2    0    0]
 [  33   47   90    8    5   15    2    3    0   11    0    0    0    0]
 [  17    6    3   40    5    8    3    0    0    0    0    0    0    0]
 [   5    2    2    3    7    7    0    0    0    3    0    0    0    0]
 [  11    3    3    1    3   47    0    0    0   13    0    1    0    0]
 [   3    1    1    1    2    0    2    0    0    1    0    0    0    0]
 [  17    3    3    0    2    2    1   23    0    9    0    1    0    0]
 [   6    0    0    1    0    0    0    0    1    1    0    0    0    0]
 [  52   17   10    0    4   21    0    7    0  347    0    0    0    0]
 [   7    1    0    0    0    0    0    0    0    0    0    0    0    0]
 [   1    0    0    0    1    0    0    0    0    0    0    2    1    0]
 [   1    0    1    1    0    0    0    0    0    0    1    0    0    0]
 [   1    0    0    0    0    0    0    0    0    0    0    0    0    0]]
```

Classification Report:

	precision	recall	f1-score	support
0	0.92	0.95	0.93	3682
1	0.83	0.84	0.83	1092
2	0.68	0.42	0.52	214
3	0.56	0.49	0.52	82
4	0.17	0.24	0.20	29
5	0.39	0.57	0.47	82
6	0.14	0.18	0.16	11
7	0.59	0.38	0.46	61
8	0.50	0.11	0.18	9
9	0.81	0.76	0.78	458
10	0.00	0.00	0.00	8
11	0.33	0.40	0.36	5
13	0.00	0.00	0.00	4
14	0.00	0.00	0.00	1
accuracy			0.86	5738
macro avg	0.42	0.38	0.39	5738
weighted avg	0.86	0.86	0.86	5738

Random Forest Model: An ensemble learning method used to classify weather conditions, predict safe flight conditions, and analyze variable importance.

Results:

- Achieved high accuracy in classifying weather conditions, with the best-performing model reaching **97% accuracy**.
- Detected significant weather anomalies that deviate from historical norms.

Key Features:

- **Feature Importance Analysis:** Highlights which weather variables (e.g., temperature, humidity) are most significant in predicting anomalies.
- **Robust to Noise:** Performs well even with noisy data, reducing the risk of overfitting.
- **Scalable:** Can handle large datasets efficiently.

Deep Learning with CNNs: CNNs were applied to classify weather conditions based on radar and satellite imagery.

Results:

- Achieved **over 90% accuracy** after 45 epochs of training.
- Demonstrated the ability to detect complex patterns in visual weather data, improving weather condition classification.

Key Features:

- **Automated Feature Extraction:** CNNs automatically learn relevant features from radar and satellite images, eliminating the need for manual feature selection.
- **Generalization:** The model generalized well to unseen data, indicating strong performance across various weather patterns.
- **Adaptable:** Can be fine-tuned for different types of weather data, including satellite images, radar scans, and time-series data.

Data Requirements

1. Satellite and Radar Imagery: To provide a visual context of changing weather patterns, enabling deep learning models like CNNs to extract meaningful patterns, like cloud formations and storm systems.
2. Real-time Weather Station Data: Allows for immediate updates to models improving the accuracy of forecasts.
3. Topographical and Climate Zone Data: Essential for understanding how physical geography impacts regional weather patterns.

Thought Experiment 1: Detecting “Out-of-Pattern” Weather Events Using Anomaly Detection

Objective: Identify unusual weather events deviating from historical patterns.

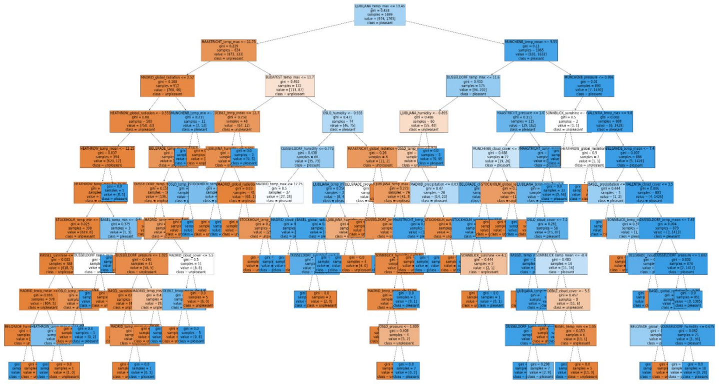
Approach:

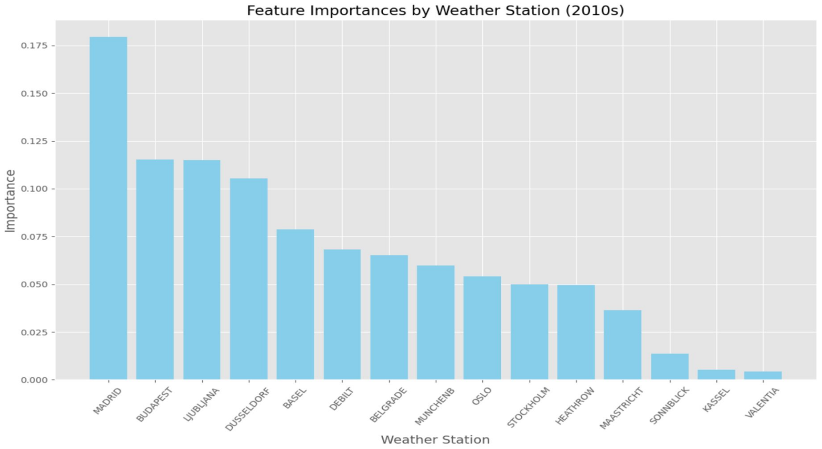
- Use Random Forest models to detect anomalies based on historical data.
- Focus on parameters like temperature spikes, rainfall changes, and unexpected snow events.

Key Questions:

1. What defines an "out-of-pattern" weather event?
2. How early can anomalies be detected?
3. How can these insights improve disaster response?

Impact: Helps predict and prepare for unusual weather events, reducing damage and improving safety measures.





Thought Experiment 2: Climate Trend Projection

Objective: Identify long-term climate trends using large datasets.

Approach:

- Apply Convolutional Neural Networks (CNNs) to analyze satellite images and radar data.
- Detect gradual changes in temperature, precipitation, and vegetation zones.

Key Questions:

1. What patterns are visible in satellite data that traditional datasets miss?
2. How accurate are CNN-based projections?
3. What thresholds indicate significant climate shifts?

Impact: Provides actionable insights for policymakers to address climate risks and adapt strategies.

Layer (type)	Output Shape	Param #
conv1d_5 (Conv1D)	(None, 14, 4)	76
dense_10 (Dense)	(None, 14, 16)	80
max_pooling1d_5 (MaxPooling1D)	(None, 7, 16)	0
flatten_5 (Flatten)	(None, 112)	0
dense_11 (Dense)	(None, 15)	1,695

Total params: 1,851 (7.23 KB)
Trainable params: 1,851 (7.23 KB)
Non-trainable params: 0 (0.00 B)

Thought Experiment 3: Geographic Safety Index

Objective: Create an index predicting safe and habitable regions in Europe based on climate risks.

Approach:

- Use Generative Adversarial Networks (GANs) to simulate future climate scenarios.
- Incorporate variables like sea-level rise, temperature increases, and extreme weather events.

Key Questions:

1. How can GAN-generated scenarios be validated?
2. What criteria should be included in a Geographic Safety Index?
3. How often should the index be updated?

Impact: Guides decision-making for relocation, investment, and infrastructure planning.

Correct Prediction - class: Sunrise - predicted: Sunrise[1.0047633e-05 1.1412430e-05 3.0133067e-04 9.9967712e-01]

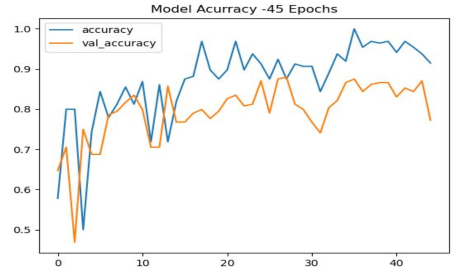
Model Performance Evaluation Using CNN

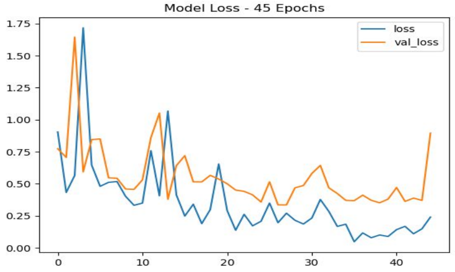
Objective: Evaluate the effectiveness of Convolutional Neural Networks (CNNs) in predicting weather patterns from large datasets, including satellite images and radar data.

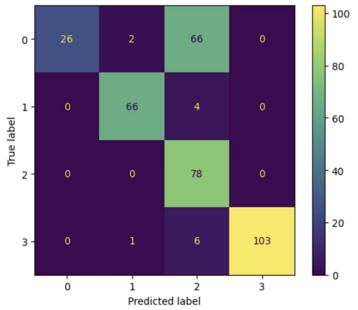
Accuracy: The model showed fluctuating accuracy early in training but improved to around 90% after 45 epochs using the ReLU activation function.

Loss: The model's training loss steadily decreased over 45 epochs, while validation loss showed more fluctuations. Adjustments to batch size and activation functions contributed to more stable loss trends

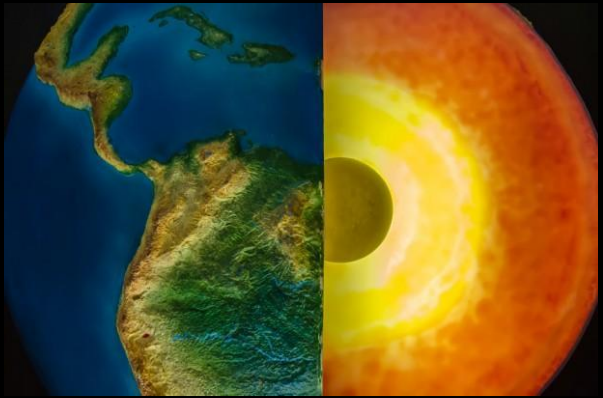
Confusion Matrix: The model's confusion matrix illustrates how accurately it predicted different weather conditions, showing both correct classifications and misclassifications between weather categories.







Recommendations & Next Steps



Thought Experiment Applications

Geographic Safety Index

- Create a **Geographic Safety Index** for Europe using GANs to predict **safe regions for living** over the next 25-50 years based on climate risks.
- Update the index regularly as new weather patterns emerge.

Out-of-Pattern Weather Event Detection

- Use **Random Forest models** to monitor weather data in real time and flag **unusual weather events**.
- This can improve disaster preparedness and reduce the impact of extreme weather conditions.

Climate Trend Projection

- Use CNN models to identify **long-term climate trends** by analyzing **satellite and radar images**.
- This insight can help policymakers plan for **future climate risks**, such as rising sea levels or shifting weather patterns.

Next Steps

1. **Deploy Models in Production:**

   Integrate the **Random Forest and CNN models** into ClimateWins' platform to start monitoring weather patterns in real time.

2. **Collect More Data:**

   Collaborate with weather agencies to obtain **satellite, radar, and historical weather data** for Europe.

3. **Monitor and Update Models:**

   Establish a process for **regular model retraining** to ensure predictions remain accurate over time as weather patterns change.

Thank You

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