WEATHER CONDITIONS AND CLIMATE CHANGE WITH CLIMATE WINS

JENNY MIELKE

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PROJECT OVERVIEW:

- **Project Background:**
  - Climate Wins is a nonprofit organization in Europe focused on addressing and reducing the effects of climate change.
  - The goal is to utilize machine learning to forecast future weather patterns including potential extreme weather events which have raised concerns in the last 10-20 years across mainland Europe.
- **Objective:**
  - Identify weather patterns outside the regional norm in Europe
  - Determine whether unusual weather patterns are increasing
  - Generate possibilities for future weather conditions over the next 25-50 years based on current trends.
  - Determine the safest places for people to live in Europe within the next 25-50 years

MACHINE LEARNING OPTIONS

CNN & RNN

How it works

- CNNs are designed to identify spatial patterns within data, whereas RNNs are designed to predict outcomes by utilizing preceding points in a sequence.

Application

- With the combination of both models, it's more efficient in predicting extreme weather events by learning both the spatial patterns (e.g., satellite images) and the sequential temporal data (e.g., historical tracking of storms).

Random Forest

How it works

- Ensemble learning algorithm that combines multiple decision trees, each trained on random subsets of the data, and aggregates the predictions to improve accuracy and reduce overfitting.

Application

- Predict meteorological variables such as temperature, precipitation, cloud coverage, humidity, or wind speed by training on historical data among Europe to determine features that contribute to weather patterns.

GANs

How it works

- Consists of two neural networks: a generator and a discriminator. The generator creates artificial data, while the discriminator attempts to distinguish between real and fake data. Over time, the generator gets better at making accurate predictions.

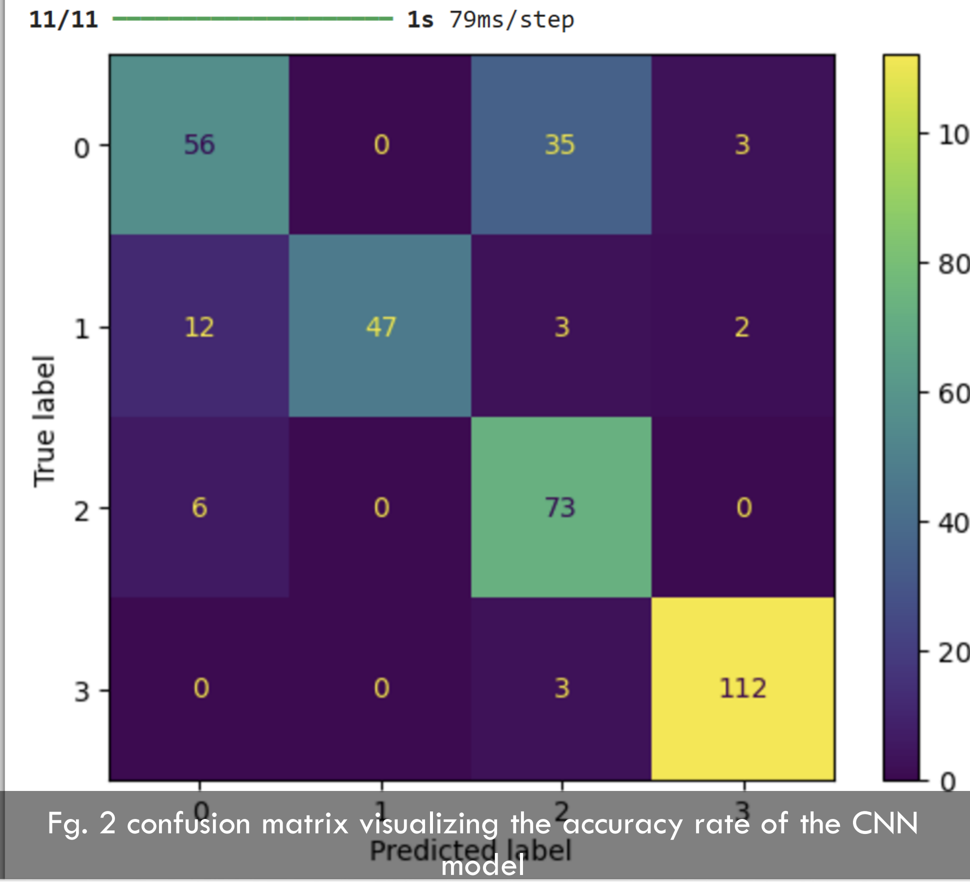
Application

- By learning the typical patterns of weather conditions, the GAN can identify unusual events such as extreme temperatures or abnormal precipitation, that differ from the expected norms.

THOUGHT EXPERIMENT 1: DETECTING WEATHER ANOMALIES

- **Goal:** Identify weather patterns in Europe that deviate from regional norms and assess whether the frequency of unusual weather events is increasing.
- **Approach:**
  - Utilize a Convolutional Neural Network (CNN) to interpret satellite images or weather maps to identify atypical weather patterns in Europe, such as temperature anomalies or storm formations.
  - The random forest model then compares these patterns with historical data to determine if they differ from regional norms. It also tracks how often these unusual events occur over time. This approach allows the combined models to detect rare weather occurrences and evaluate if their frequency is rising.
- **Data Required:** Historical climate wins weather data, satellite images

Fg. 1 illustrates a satellite image to detect weather anomalies



Fg. 2 confusion matrix visualizing the accuracy rate of the CNN model

APPLICATION OF CNN & RANDOM FOREST

THOUGHT EXPERIMENT 2: PREDICTING FUTURE WEATHER

- **Goal:** Generate possibilities for future weather conditions over the next 25-50 years based on current trends.
- **Approach:**
  - A Recurrent Neural Network (RNN) can be used to analyze historical weather data, recognizing patterns and trends over time to predict future conditions. It processes sequential data, such as temperature or precipitation, to predict both short-term and long-term trends.
  - A Generative Adversarial Network (GAN) can generate new weather scenarios by learning from existing data and creating realistic variations, which helps model different possible futures. While RNNs forecast overall trends, GANs examine a vast number of possible outcomes, providing a more comprehensive outlook on future weather possibilities.
- **Data Required:** Historical climate wins data, geospatial and topographic data

APPLICATION OF RNN AND GAN

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144/144 ━━━━━━━━━━━━━━━━━━━━ 1s 3ms/step
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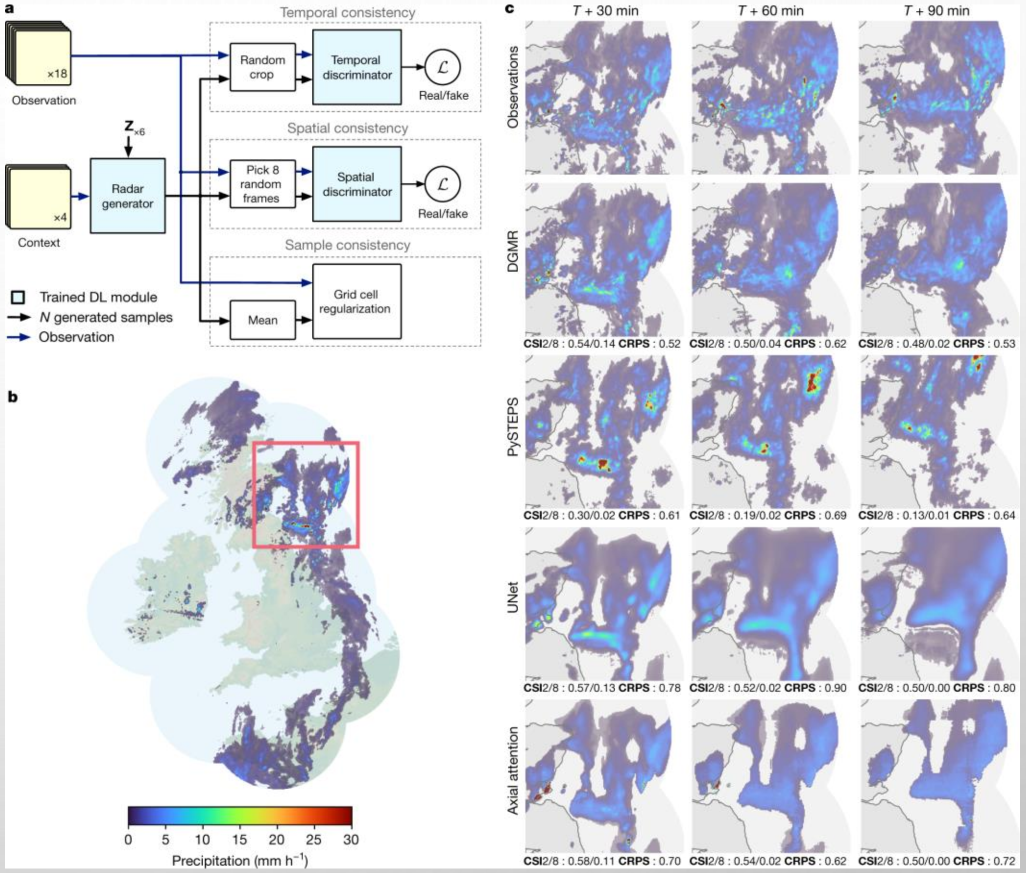
predictions / True	BASEL	BELGRADE	DEBILT	DUSSELDORF	HEATHROW	KASSEL	LJUBLJANA \
BASEL	1	9	0	1	0	2	1
BELGRADE	0	2	1	0	0	1	0
BUDAPEST	0	1	0	0	0	0	0
DEBILT	0	0	0	0	0	0	0
DUSSELDORF	0	0	0	0	0	0	0
HEATHROW	0	0	0	0	0	0	0
KASSEL	0	0	0	0	0	0	0
LJUBLJANA	0	0	0	0	0	0	0
MAASTRICHT	0	1	0	0	0	0	0
MADRID	0	6	1	0	1	2	0
MUNCHENB	0	0	0	0	0	0	0
OSLO	0	0	0	0	0	0	0
STOCKHOLM	0	0	0	0	0	0	0
VALENTIA	0	0	0	0	0	0	0

predictions / True	MADRID	OSLO	STOCKHOLM	VALENTIA
BASEL	1230	6	1	1677
BELGRADE	865	3	1	26
BUDAPEST	169	0	0	0
DEBILT	73	0	0	0
DUSSELDORF	30	0	0	1
HEATHROW	70	1	0	3
KASSEL	7	0	0	0
LJUBLJANA	44	1	0	1
MAASTRICHT	7	0	0	0
MADRID	171	7	4	139
MUNCHENB	9	0	0	0
OSLO	8	0	0	0
STOCKHOLM	2	0	0	0
VALENTIA	3	1	0	0

Fg. 1 Confusion matrix provides accuracy rates on predictions on weather stations in Europe.

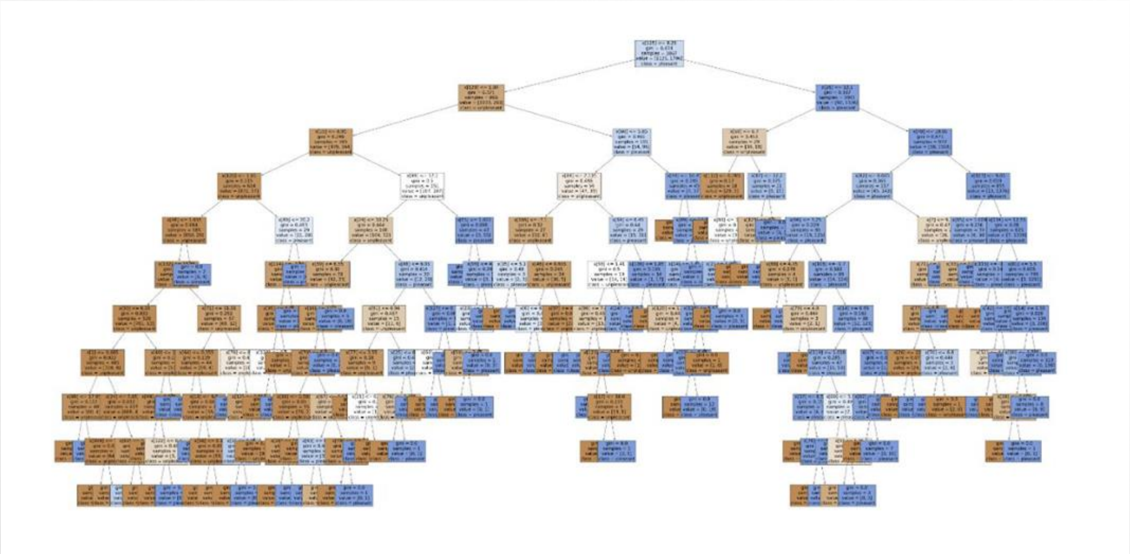


Fg. 2 GAN chart comparing weather images

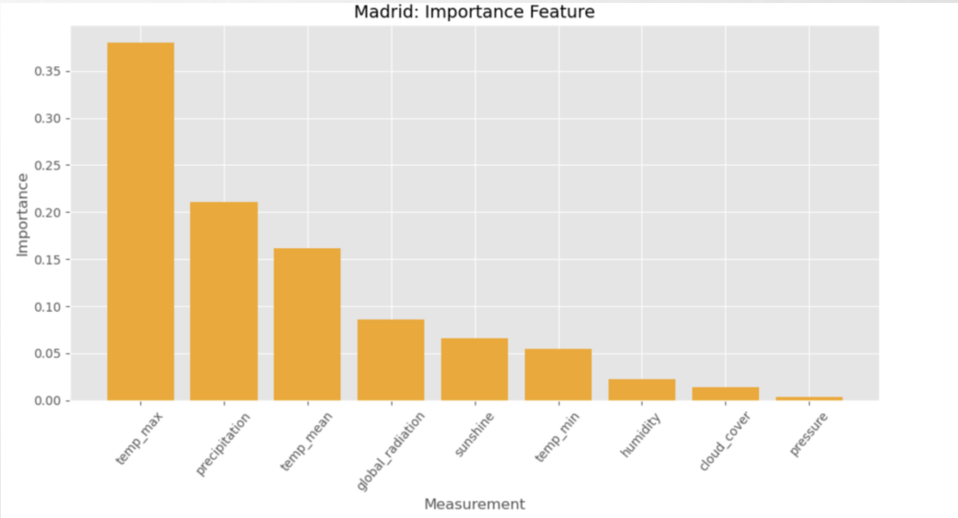
THOUGHT EXPERIMENT 3: DETERMINE SAFEST PLACES TO LIVE

- **Goal:** Determine the safest places for people to live in Europe within the next 25-50 years
- **Approach:**
  - A GAN can simulate various future scenarios for factors such as climate, natural disasters, and population growth across Europe.
  - A Long-Short Term Memory (LSTM) network examines past data to predict how these factors might evolve over the next 25-50 years.
  - A random forest algorithm then processes this data to identify regions that are likely to remain safe based on these predictions. Together, they provide a holistic approach to pinpoint the safest places to live in the long term.
- **Data Required:** historical data, climate model data, elevation data

APPLICATION OF GAN, LTSM, RANDOM FOREST



Fg 1. Random forest model classifying weather predictions



Fg. 2 Bar graph providing insights on which feature has the most importance in random forest

SUMMARY

Thought Experiment 1

- **Pros**
  - Improved accuracy due to utilizing the strengths of both models in classification and feature extraction.
  - Reduced risk of overfitting with random forest
- **Cons**
  - Difficult to interpret due to complexity or noise
  - Potential to increase computational complexity

Thought Experiment 2

- **Pros**
  - RNN models are effective at modeling time-series data such as historical trends which allows them to capture weather patterns.
  - GAN generates diverse and realistic future weather scenarios based on trends.
- **Cons**
  - GANs are difficult to train effectively
  - With forecasting a 25-50 year span as well as the combination of the models, this may require extensive computational resources.

Thought Experiment 3

- **Pros**
  - Similar to RNNs, LSTM models excel at capturing long-term dependencies in time-series data, making them well-suited for forecasting trends such as climate change or natural disasters.
  - Can create diverse and realistic future scenarios of environmental conditions
- **Cons**
  - Training Complexity
  - If there are any incomplete to rare climate events, there can be inaccurate predictions.
  - With the combination of the 3 models, there is a risk of overfitting

RECOMMENDATIONS / NEXT STEPS

- **Thought Experiment 1 Most Potential:**
  - The combination of CNNs and Random Forest models offers a powerful way to analyze weather patterns in Europe.
  - The CNN extracts relevant features from complex satellite or weather map data, while the Random Forest assesses these features against historical data to identify anomalies and trends.
  - This approach has the potential to provide highly accurate insights into the frequency and nature of unusual weather events, which is imperative for understanding climate change.
  - Although there are challenges in interpretability and computational cost, the benefits outweigh these concerns.
- **Next steps:**
  - Foster collaboration with meteorological agencies to collect additional data

THANK YOU!