Climate Wins

Predicting Climate Change with Machine Learning

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Objectives

Identifying Regional Anomalies:

Detecting weather patterns that fall outside normal regional trends to understand emerging risks.

Assessing the Increase in Unusual Weather Events:

Analyzing trends to determine if extreme weather occurrences are becoming more frequent or severe.

Forecasting Future Climate Scenarios:

Projecting future weather conditions over the next 25 to 50 years based on current climate trends.

Identifying Safe Havens:

Determining the safest places for people to live by understanding which areas will be most resilient to climate change in the coming decades.

Machine Learning Tools for Analysis

Random Forest	CNNs and RNNs	GANs (Generative Adversarial Networks)
Collection of decision trees, forming an ensemble learning algorithm that trains multiple models simultaneously. It combines predictions from individual trees (trained on random data samples) to produce accurate results and ranks feature importance effectively.	CNNs detect spatial patterns, ideal for analyzing visual or geographical weather data. RNNs process temporal data, making them suitable for modeling sequential weather trends like seasonal changes.	Use a generator and discriminator to create realistic synthetic data. This can augment datasets, improving model training and performance, especially for rare weather events.

Strategic Pipelines

Thought Experiments

1

Classify Unusual Weather

Detect and classify rare weather patterns using CNN for satellite imagery and Random Forest for integrated weather analysis, emphasizing recall to avoid missing severe events

2

Tracking Trends in Extreme Weather

Use CNNs and RNNs to analyze weather patterns over time, and GANs to simulate rare events, tracking trends to assess the growing frequency and severity of extreme weather.

3

Projecting Safe Living Areas

Analyze satellite imagery with CNNs and k-means clustering to evaluate regional vulnerability to natural disasters, identifying high-risk areas and safer zones for habitation.

Classify Unusual Weather

Thought Experiment 1

The goal here is to detect unusual weather patterns that deviate from normal regional trends, identifying emerging risks.

Using CNNs to analyze satellite images for anomalies in weather (such as severe storms or unseasonal temperatures) assists with identifying these outliers. By integrating historical weather data, the model can capture anomalies across time, helping to predict or identify unusual weather patterns.

Algorithms Needed:

CNN (Convolutional Neural Network) + Random Forest

Data Needed:

Historical weather data (temperature, pressure, wind speed anomalies) and satellite imagery of severe weather events

Approach:

Use CNNs to detect unusual weather patterns in satellite images. Merge CNN outputs with historical data for Random Forest classification.

How to Evaluate:

Evaluate performance using a confusion matrix and metrics like accuracy, precision, and recall.

Potential Drawbacks:

Rare weather events may bias the model. Address imbalance with class weighting and prioritize recall to reduce false negatives

Tracking Trends in Extreme Weather

Thought Experiment 2

This thought experiment uses CNNs and RNNs to track and analyze extreme weather events, identifying whether their frequency and severity are increasing over time. By combining spatial data from satellite and radar imagery with time-series analysis, we assess trends in unusual weather patterns, helping us understand the potential future impact of extreme events.

Algorithms Needed:

GAN, CNN, + RNN

Data Needed:

Radar and satellite data, historical trends of temperature, precipitation, and atmospheric patterns. Include rare event data where available or use GAN-generated synthetic data.

Approach:

Use CNNs to analyze radar and satellite images to detect unusual weather patterns. An RNN will then be employed to track these patterns over time, helping to assess whether extreme weather events are becoming more frequent or severe. Leverage GANs to generate synthetic data for rare events, ensuring the model can better predict and identify emerging trends in extreme weather over longer time spans.

How to Evaluate:

Evaluate the RNN's ability to capture time-based patterns and track changes in the frequency and intensity of extreme events. Metrics like precision, recall, F1-score, and loss functions will help assess prediction accuracy. Compare predictions with historical records to validate the trend of increasing unusual weather occurrences.

Potential Drawbacks:

GANs may generate unrealistic or redundant data, which could affect model performance. RNNs might also struggle with long-term dependencies in very large datasets, requiring careful tuning and validation.

Projecting Safe Living Areas

Thought Experiment 3

This thought experiment focuses on projecting future weather conditions over the next 25 to 50 years based on current climate trends and identifying the safest, most climate-resilient regions for habitation.

Algorithms Needed:

CNN and geospatial clustering (k-means)

Data Needed:

Historical weather data, flood and fault line maps, elevation metrics, climate projections (Copernicus CDS, IPCC-DDC).

Approach:

Use CNNs to identify high-risk zones based on current satellite imagery and patterns. Overlay climate projection data (e.g., future precipitation shifts, temperature changes). Apply k-means to categorize regions by risk, highlighting resilient areas.

How to Evaluate:

Compare clustered risk classifications to historical and projected data. Validate clustering quality using silhouette scores. Cross-reference with observed safe and vulnerable areas.

Potential Drawbacks:

Climate change variability requires frequent data updates. Regional factors like infrastructure changes may alter risk profiles over time.

Guiding Climate Wins’ Strategy

A phased approach implementing various machine learning models to answer key objectives

Phased Approach

Phase 1:

Data Collection & CNN Setup

Collect and preprocess satellite and radar imagery.

Combine imagery data with historical weather data to create a comprehensive training dataset.

Develop and train a CNN for detecting anomalies.

Key Outcome: A trained CNN model generating reliable probabilities or flags for unusual weather, ready for integration with additional analytical models.

Phase 2:

Classify Unusual Weather

Integrate CNN outputs (e.g., anomaly probabilities or flags) with historical weather data.

Train a Random Forest model to classify specific types of unusual weather events (e.g., extreme temperatures, heavy rainfall).

Key Outcome: Early warning system for detecting unusual weather events.

Phase 3:

Tracking Trends in Extreme Weather

Utilize Recurrent Neural Networks (RNNs) to analyze and model weather trends over time.

Generate synthetic data using GANs to fill gaps in rare event data, enhancing model accuracy.

Key Outcome: Assessment of extreme weather trends and intensities over time.

Phase 4:

Project Safe Living Areas

Apply k-means clustering to classify regions by climate risk (e.g., flooding, extreme heat).

Integrate additional spatial datasets, such as elevation, flood zones, and fault lines, to refine analysis.

Key Outcome: Identification of high- and low-risk zones for climate-resilient living.

Thank You

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