AI for Local Climate Monitoring and Prediction: Deep Learning for Anomaly Detection and Forecasting

SORBONNE UNIVERSITY ABU DHABI

1. AI to Handle Climate Data

Climate change is one of the most pressing challenges of our time, with extreme weather events, temperature anomalies, and environmental shifts becoming increasingly frequent. The ability to detect climate anomalies early and accurately forecast future trends is crucial for mitigating adverse effects. The proliferation of weather observatory sites, including satellites, weather stations, radars, and balloons, has significantly expanded the availability of climate data. These datasets provide critical insights into oceanic changes (e.g., water levels, glacial melt), terrestrial shifts (e.g., forest fires, desertification, flooding, drought), and atmospheric composition variations (e.g., carbon emissions, air pollution).

Traditional climate modeling techniques rely heavily on physics-driven approaches, built on intricate mathematical frameworks and large-scale computer simulations that integrate knowledge from meteorology, climatology, and geophysics. However, these models often struggle with high-dimensionality, non-linearity, and unpredictable variations in observed and simulated climate data.Despite the vast amounts of available data, significant uncertainties remain regarding climate change and its short- and long-term impacts. Predicting sudden extreme weather events at a localized scale remains a major challenge. Two critical limitations of conventional physics- driven climate models are:

- Short-term impact analysis: The need for real-time anomaly detection and monitoring.
- Long-term impact forecasting: The challenge of accurately predicting localized climate trends.

Addressing these limitations requires integrating advanced deep learning techniques, which can effectively capture complex patterns in climate data and enhance predictive capabilities.

2. Climate Anomaly Detection

Climate anomaly detection involves identifying unusual deviations from expected climate patterns. Conventional statistical methods such as Principal Component Analysis (PCA), Gaussian Mixture Models (GMM), and Autoregressive Integrated Moving Average (ARIMA) models have been widely used. However, they often fail to capture non-linear dependencies in large-scale climate datasets. Deep learning techniques, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and Transformer models, have demonstrated superior performance in time-series forecasting. These methods can capture spatial and temporal dependencies in climate data more effectively than classical approaches.

3. Our Approach: AI-driven Anomaly Detection for Forecasting

3.1 Local Climate Data

This project will utilize a blend of publicly available and proprietary climate datasets, accessible for academic research purposes. The sources include: Copernicus Data Space Ecosystem, Sentinel Hub, NASA EOS, ECMWF, INPE Brazil, USGS, NOAA, AWS, MAXAR, local meteorological station data, our own measurements (IoT devices, drones, …) and local urban and costal collected data (water level and temperature, street or soil temperature, …) from the sites under investigations.

3.2. Deep Learning Models

This research will explore various AI-based architectures for anomaly detection and forecasting [6].

- For anomaly detection, unsupervised learning techniques such as Autoencoders, Variational Autoencoders (VAEs) [4], and Generative Adversarial Networks (GANs) will be employed to identify deviations from expected climate patterns.
- For time-series forecasting [2], the study will leverage advanced deep learning models, including LSTMs and Gated Recurrent Units (GRUs) for sequential data processing. Transformer-based models will be considered to enhance long-range dependencies, while Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) [3, 5] will be integrated to capture spatial and temporal dependencies in climate data. Additionally, hybrid architectures will be explored to combine spatial and temporal analysis for more robust forecasting.

3.3. Anomaly Detection Approach and Forecasting Strategy

The methodology will begin by establishing a baseline of normal climate behavior using historical local patterns. Deep learning models will then be trained to detect outliers and abnormal events in temperature, precipitation, and extreme weather conditions. To ensure reliability, domain knowledge will be incorporated to validate detected anomalies. For forecasting, models will be trained on historical climate data to predict future trends, leveraging transfer learning techniques to adapt to new datasets. The evaluation process will involve rigorous performance assessment across various metrics to ensure accuracy and generalizability:

- We will explore methods for integrating these models or their outputs. For example, in [1], separate CNNs were trained for wind and pressure data before being fused into a final network, which was then re-trained to predict hurricane trajectory displacement over 24 hours.
- We will investigate the use of Graph Neural Networks (GNNs) and Graph Convolutional Networks (GCNs) for climate time series [3, 5], assessing their adaptability and potential benefits in improving forecasting accuracy.
- We will also consider the applicability of anomaly detection techniques used in trust analysis for AI, such as Neural Collapse properties and specific metrics, alongside event detection methods drawn from computer vision for practical applications.

4. Expected Contributions and Real-World Applications

This research aims to develop a robust AI-driven framework for climate anomaly detection, enhancing the accuracy and reliability of climate forecasting models. By enabling early anomaly detection, the project will contribute to climate change mitigation efforts and provide actionable insights for local climate adaptation strategies. A key focus will be on applying this framework to specific locations under investigation, with an emphasis on urban climate analysis for the City of Abu Dhabi. Given its extreme temperatures, even minor climate fluctuations can have significant consequences. Our AI-driven approach to local climate monitoring and prediction will offer valuable applications, including:

- Enhancing solar farms and smart irrigation management by optimizing energy and water distribution based on precise climate forecasts. Mitigating climate-related disruptions to critical industries such as oil extraction sites and airport operations (e.g., extreme heat has been responsible for 24% of summer flight delays in Southern Europe.).
- Supporting urban planning and infrastructure resilience by addressing vulnerabilities in electric vehicle charging stations and locations, mitigating the Urban Heat Island Effect (solar radiation raising inner city temperature and energy demand), and improving public health and mobility in high-temperature environments. By integrating AI-driven climate modeling into urban and industrial settings, this research will provide tangible benefits for policymakers, businesses, and local communities, fostering a more climate-resilient future.

This Phd these will bridge the gap between AI and climate science by integrating deep learning methods for anomaly detection and forecasting. The outcomes will support climate policy decisions, enhance early warning systems, and contribute to a more sustainable approach to environmental monitoring.

5. Advisors

- **Professor Dr. Abdenour Hadid, SCAI - Sorbonne University of Abu Dhabi**.
  3 last publications: [ICMLA2022] A Wavelet-based Transformer Framework for Univariate Time Series Fore- casting, IEEE international conference on Machine Learning and Applications. [ICMLA2022] Knowledge-based Deep Learning for Modeling Chaotic Systems, IEEE international conference on Machine Learning and Applications. [Computer Vision and Image Understanding] Age estimation from faces using deep learning: A comparative analysis.
- **Associate Prof. Dr. Rachid Rebiha, "Maitre de Conference" CNAM Paris**.
  3 publications: [AI and Security] Semantic Malware Resistance Using Inductive Invariants. Journal of Forensic Computer Science. [ML and Forecasting] Digital Money Index Symposium, London UK 2017. Citi Digital Money Symposium annual associated report. [AI, Agent] An Ant Colony Verification Algorithm. Conf. IEEE. Intelligent Systems Design and Applications.
- **Professor Dr. Samia Saad-Bouzefrane - Director of Research Dpt. Computer Science, CNAM Paris**.
  3 publications: [ANT2024] Enhancing privacy in VANETs through homomorphic encryption in machine learning applications [WISTP2024] Privacy Preserving Federated Learning: A Novel Approach for Combining Differential Privacy and Homomorphic Encryption [ETCA2023] Application of Homomorphic Encryption in Machine Learning.

References

[1] Sophie Giffard-Roisin, Mo Yang, Guillaume Charpiat, Christina Kumler Bonfanti, Balazs Kegl, and Claire Monteleoni. Tropical Cyclone Track Forecasting using Fused Deep Learning from Aligned Reanalysis Data. Frontiers in Big Data, 3, 2020.

[2] AmjadIqbalandRashidAmin.Timeseriesforecastingandanomalydetectionusingdeeplearning.Computers & Chemical Engineering, 182, 2024.

[3] Alex Romanova. Gnn graph classification for time series: A new perspective on climate change analysis. In Proceedings of the 2024 9th International Conference on Machine Learning Technologies, 2024.

[4] Saumya Sinha, Sophie Giffard-Roisin, Fatima Karbou, Michael Deschatres, Anna Karas, Nicolas Eckert, Cecile Coleou, and Claire Monteleoni. Variational autoencoder anomaly-detection of avalanche deposits in satellite sar imagery. In Proceedings of the 10th International Conference on Climate Informatics, 2021.

[5] Yin Yu, Peiyuan Li, Daning Huang, and Ashish Sharma. Street-level temperature estimation using graph neural networks: Performance, feature embedding and interpretability. Urban Climate, 56, 2024.

[6] Zahra Zamanzadeh Darban, Geoffrey I. Webb, Shirui Pan, Charu Aggarwal, and Mahsa Salehi. Deep learning for time series anomaly detection: A survey. ACM Comput. Surv., 57(1), 2024.