Using Machine Learning to Forecast Favourable vs. Dangerous Weather for a European Non-Profit

Case Study: Predictive Modelling for Climate Change Adaptation



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- The Challenge: Objective & Business
 The Outcome: Accuracy & Critical Indicators
 The Process: Key Questions & Methodology
 The Impact: Strategic Insight & Recommendations
- 3. Key Visuals: Evidence from Analysis 6. Q&A

PROACTIVE RESPONSE TO EXTREME WEATHER in the EU

Objective: ClimateWins, a European non-profit organization, needed to assess machine learning tools for predicting the consequences of climate change, specifically the increase in extreme weather events.

Business Context: As a resource-constrained non-profit focused on humanitarian response, they required a cost-effective, data-driven method to anticipate dangerous conditions and inform their operational strategy.



PROCESS A

KEY QUESTIONS

IS THERE A QUANTIFIABLE WARNING TREND?

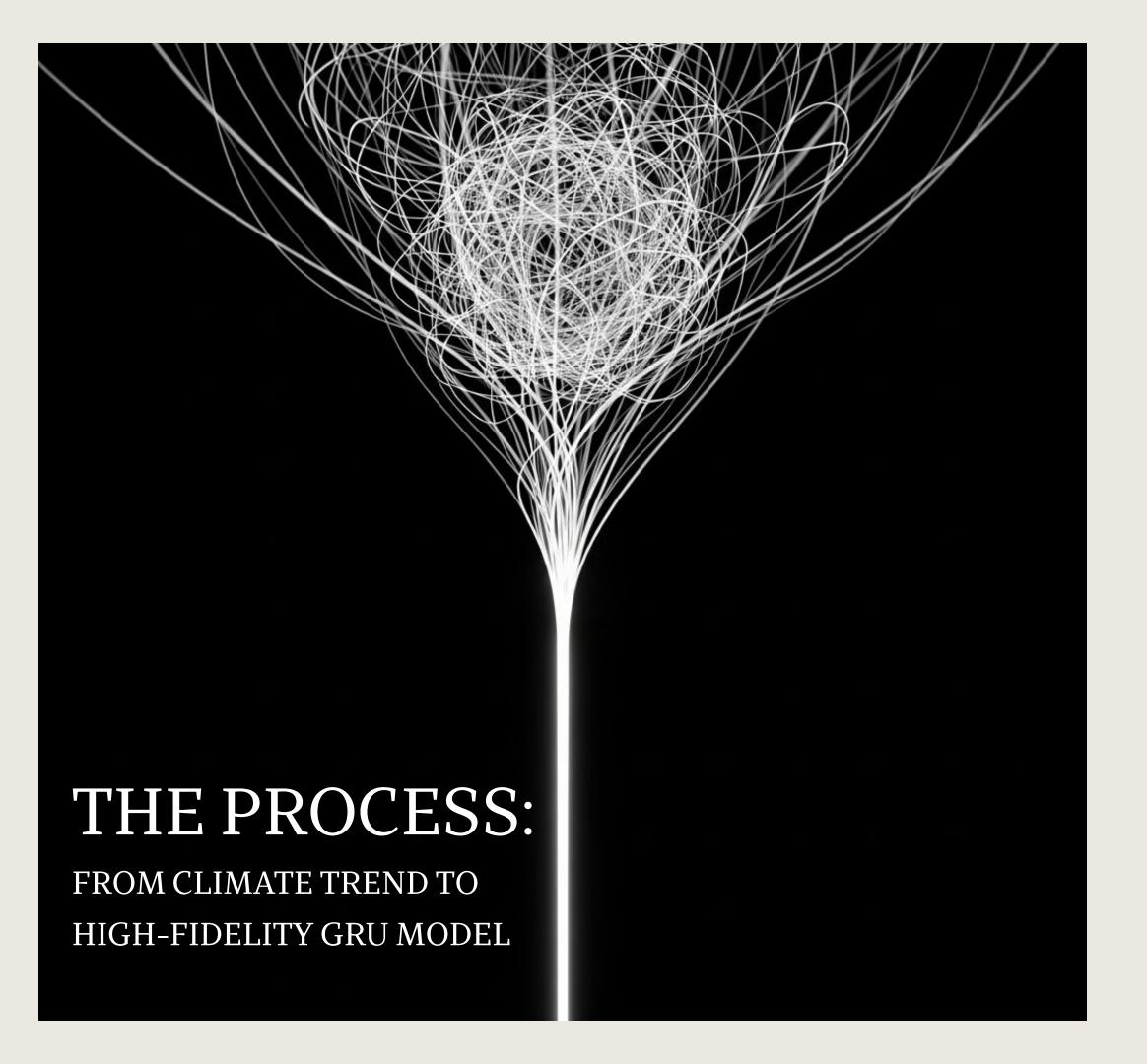


CAN ANY MODEL RELIABLY IDENTIFY SAFE AND DANGEROUS DAYS?



WHICH STATIONS & **VARIABLES MATTER** MOST?





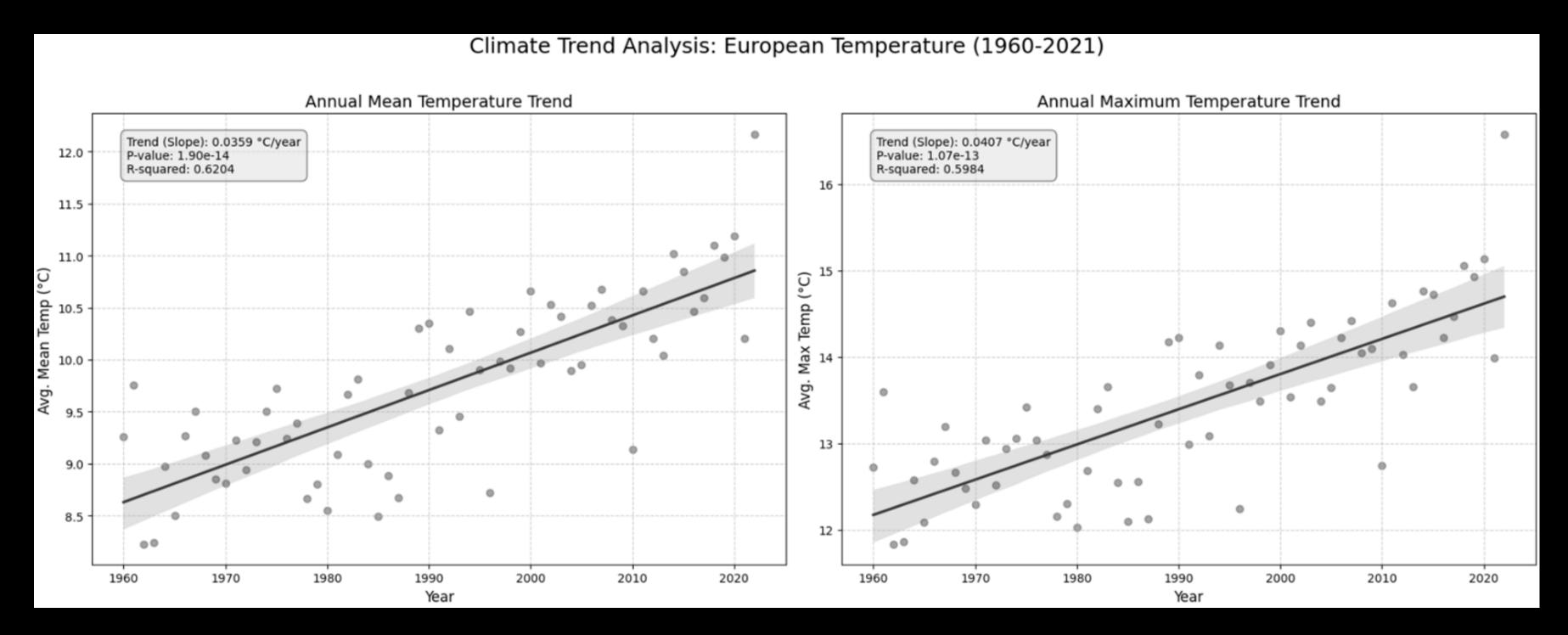
METHODOLOGY

The project involved statistical trend analysis and a comparative evaluation of machine learning models (Random Forest, CNN, RNN, LSTM, and GRU) implemented in Python using Pandas, Scikit-learn, and Keras.

KEY FINDINGS

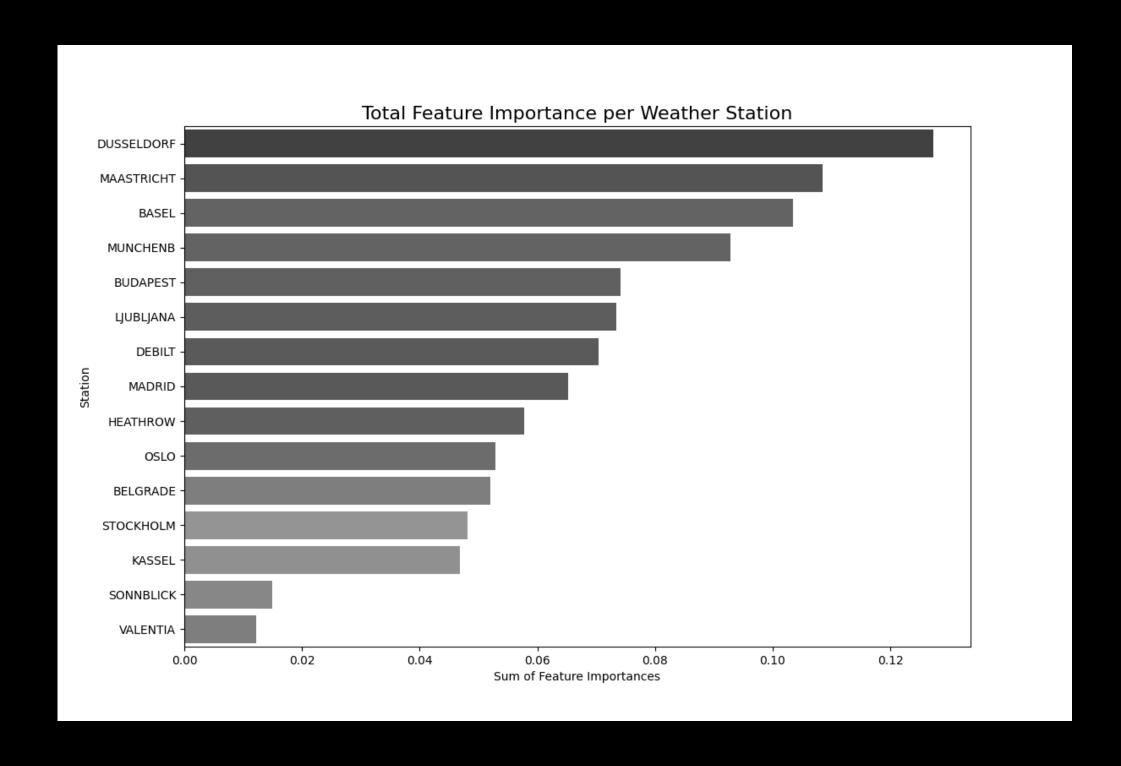
Analysis confirmed a statistically significant warming trend since 1960. While a Random Forest model provided high interpretability, identifying key stations and variables, an optimized Gated Recurrent Unit (GRU) model proved to be the most accurate (98.1%) for the complex multi-station prediction task.

Climate Trend Analysis Plot



Exploratory data analysis confirmed a significant, long-term increase in both mean and maximum temperatures across Europe, validating the project's core premise and the need for predictive tools.

Feature Importance per Station Chart



The Random Forest model identified Düsseldorf, Maastricht, and Basel as the most influential "hub" stations, making them critical for data monitoring and strategic resource allocation.

GRU Model Outperforms All Architectures

A comprehensive search across multiple deep learning architectures revealed that a tuned GRU model achieved the highest accuracy (98.1%) on the complex multi-station prediction problem.

	loss	accuracy	training_time
GRU_Tuned	0.052150	0.980740	580.737262
LSTM_Tuned	0.097407	0.963428	591.286209
Dense_Tuned	0.089471	0.962469	84.746660
RNN_Tuned	0.100606	0.958402	250.290498
CNN_Tuned	0.104686	0.956993	75.744792

THE OUTCOME: STRATEGIC TOOL for DISASTER PREPAREDNESS

98,1% ACCURACY

CRITICAL HUBS & INDICATORS

STRATEGIC INSIGHT



Developed a tuned GRU model that successfully predicts favorable vs. dangerous conditions across 15 European locations, establishing a strong proof-of-concept.



Analysis revealed that
Düsseldorf, Maastricht, and
Basel are the most predictive
stations, while atmospheric
pressure and minimum
temperature are the most
influential variables.



The model provides a robust, data-driven foundation for a proactive alert and resource deployment system, shifting ClimateWins from a reactive to a predictive operational stance.





OPERATIONALIZE 01 the GRU MODEL

Implement the high-accuracy GRU model as a proof-of-concept for a regional weather alert system for humanitarian teams.

PRIORITIZE SENSOR DATA

Prioritize investment in high-quality sensor data for the top 3 predictive stations, focusing on pressure and temperature monitors to maximize ROI.



02

DEVELOP 03 A RISK SCORE

Evolve the binary "pleasant/dangerous" label into a multi-class "Operational Risk Score" (e.g., Low, Medium, High) to provide more nuanced guidance for mission planning and resource pre-positioning.



EXPLORE HYBRID

A hybrid CNN-GRU model could be a robust next architecture to test.



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Thank you!

Project file: <u>03_Data_Research_Project_Plan.pdf</u>
Detailed Report: <u>ml_pipeline_multimode.ipynb</u>
Direct link to GitHub: <u>climate-weather-prediction_vo2</u>