ML Lab Research Proposal
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1. Problem Statement

Accurately predicting extreme weather events (e.g., heatwaves, storms) remains difficult due to the separation of short-term sensor data and long-term climate patterns in existing models. This project aims to improve prediction accuracy by combining both data types into a unified AI model. Better forecasts can reduce economic damage and improve public safety.

2. Proposed Approach

We will develop a hybrid model that combines a recurrent neural network (RNN/LSTM) for short-term temporal patterns with a gradient boosting model for long-term climate trends. The outputs will be fused using a meta-model (ensemble method). This approach is chosen because LSTMs handle time-series dependencies well, while boosting models capture structured, non-linear relationships. The ensemble allows leveraging strengths of both.

3. Dataset

We will use publicly available weather datasets such as NOAA or Kaggle weather data, including temperature, humidity, wind speed, and precipitation over time. The dataset will include multiple years of hourly or daily observations. Preprocessing will involve handling missing values, normalization, and feature engineering (e.g., rolling averages, lag variables).

4. Evaluation Metrics

Model performance will be evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) for prediction accuracy. For extreme event detection, we will use precision, recall, and F1-score. These metrics ensure both overall accuracy and effectiveness in identifying rare events.

5. Compute Requirements

Training is expected to take 1–3 hours on a standard GPU (e.g., NVIDIA T4) or several hours on CPU. Memory requirements are moderate (~4–8 GB RAM). Dependencies include Python libraries such as TensorFlow/PyTorch, scikit-learn, and pandas.

6. Expected Deliverables

By the end of two weeks, we will produce a trained hybrid model, a short research report summarizing methods and results, and a simple demo (e.g., notebook or visualization) showing predictions on test data.

7. Risk & Mitigation

A key risk is insufficient improvement over baseline models due to limited data or time. To mitigate this, we will implement a simpler baseline model (e.g., linear regression or single ML model) for comparison. If the hybrid model underperforms, we will refine features or reduce model complexity to ensure stable results.