EXPLAINABLE AI IN WEATHER FORECASTING

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PROBLEM STATEMENT

- Traditional AI/ML models in weather forecasting are highly accurate but lack interpretability.
- This lack of transparency limits their usefulness in:
  - Disaster preparedness
  - Public communication
  - Policy decisions
- Meteorologists, government, public need trustworthy, interpretable predictions.

PROJECT OBJECTIVES

- This project integrates Explainable AI (XAI) to enhance the transparency and trustworthiness of AI-driven weather predictions.
- We use models like Random Forest, LSTM, and CNN for pattern analysis, alongside XAI tools such as SHAP, LIME, and attention mechanisms to interpret model decisions.
- This approach makes predictions more understandable and actionable for meteorologists and stakeholders. Future work aims to incorporate real-time data and improve adaptability for extreme weather events.

PROJECT WORKFLOW

Stages:

1. Data Collection
2. Preprocessing
3. Feature Engineering
4. Model Training
5. Forecast Prediction
6. Explainability Analysis (XAI)

Parameters:

- Temperature (°C)
- Humidity (%)
- Wind Speed (m/s)
- Pressure (hPa)
- Precipitation (mm)
- Dew Point (°C)

EXPLAINABILITY TOOLS

SHAP (SHapley Additive exPlanations)

- Global & local feature importance
- Works with any model
- Based on game theory

LIME (Local Interpretable Model-Agnostic Explanations)

- Explains individual predictions
- Trains a simple local surrogate model

Grad-CAM (for CNNs)

- Heatmaps over satellite images
- Shows important regions contributing to prediction

CASE STUDY 1 – RAINFALL PREDICTION (RANDOM FOREST + SHAP)

- Input: Temperature, Pressure, Humidity, Wind
- SHAP Results:
  - High humidity → positive contribution to rainfall
  - Rising pressure → negative contribution

CASE STUDY 2 – CYCLONE DETECTION (CNN + GRAD-CAM)

- Input: Satellite image of cloud cover
- Output: Predicted cyclone presence
- Grad-CAM shows focus on:
- Dense cloud spiral
- Low-pressure centers

CASE STUDY 3 – TEMPERATURE TREND (LSTM + LIME)

- Input: 24-hour sequence of features
- Prediction: Next hour’s temperature
- LIME:
  - Explains specific forecast
  - Identifies sharp drop in dew point as key factor

Real-World Benefits

- Meteorologists: Understand patterns driving forecasts
- Policy Makers: Issue timely weather warnings
- General Public: Easy-to-read visuals (heatmaps, summaries)
- Emergency Response: Faster reaction to extreme events

Future Scope

- Real-time data integration (weather APIs)
- Predicting rare/extreme events (cyclones, floods)
- Interface for public: Natural-language summaries of forecasts
- Multimodal models (text + image + audio alerts)

THANK YOU