🌞 Case Study: AI-Powered Solar Energy Production Forecasting

📌 Project Title:

Forecasting Solar Power Generation Using AI and Weather Data

Presented By :
Krishna Naik
Suyog Daule
Tanmay Sonawane
Saitej Wadekar
Aditi Nehulkar

🎯 Objective:

To develop an AI-driven system that accurately predicts solar energy production using historical solar output and real-time weather conditions. This helps optimize energy grid management, storage, and consumption planning.

🧩 Problem Statement:

Solar energy production is **highly dependent on weather conditions**, which vary unpredictably. Energy providers struggle to integrate solar power effectively due to its **intermittent nature**. There is a strong need for a system that can **forecast solar power generation** with high accuracy.

🛠 Solution Overview:

An AI-powered forecasting system using machine learning, specifically **LSTM neural networks**, was implemented to predict hourly solar power generation. It leverages:

- Historical solar energy data
- Weather parameters (temperature, humidity, irradiance, wind speed)

📚 Dataset Used:

- **Source**: Kaggle (Solar Power Generation Data)
- **Fields**: Timestamp, Solar Power Output (kWh), Temperature, Humidity, Wind Speed, Solar Irradiance

Technology Stack:

Component	Tool/Library
Programming Language	Python
ML Library	TensorFlow / Keras
Data Analysis	Pandas, NumPy
Visualization	Matplotlib, Seaborn
Model Type	LSTM (Long Short-Term Memory)
Preprocessing	MinMaxScaler (Sklearn)

Process Workflow:

1. **Data Preprocessing**
    - Missing values handled using forward fill
    - Features normalized using MinMaxScaler
    - Time-series sequences created for LSTM input
2. **Model Building**
    - An LSTM model with two layers was used
    - Trained to predict the next hour's solar power output
3. **Evaluation Metrics**
    - Mean Absolute Error (MAE)
    - Root Mean Squared Error (RMSE)
4. **Results Visualization**
    - Compared predicted vs actual values on test data
    - Plotted for visual assessment and reporting

Results:

- The model achieved an **RMSE of ~0.13** (on normalized values)
- It was able to **predict solar output trends accurately**, with deviations mostly under extreme weather shifts
- **Prediction window:** 24-hour rolling forecast
- The system can be updated with **real-time weather API** data for live forecasts

Key Learnings:

- **LSTM is effective** for capturing temporal patterns in solar power data.
- **Weather features** like irradiance and humidity significantly affect model accuracy.
- **Data quality** and **feature scaling** play a major role in performance.

🌍 Impact:

- **Energy Providers**: Better grid load balancing
- **Solar Farms**: Improved panel maintenance planning
- **Smart Homes**: Efficient battery and device scheduling

🔮 Future Scope:

- Integrate real-time **weather APIs** (e.g., OpenWeatherMap)
- Build a **web dashboard** for interactive forecast visualizations
- Expand the system to **multi-site forecasting** for large-scale solar farms