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Green Sentry - Weather App

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Abstract: Accurate hyper local weather forecasting remains one of the most challenging tasks in meteorology due to high spatial variability, changing climate patterns, and limitations of conventional statistical approaches. Traditional forecasting systems largely rely on satellite observations, numerical weather prediction models, and coarse-grained climate datasets, which fail to provide localized predictions required for agriculture, logistics, disaster management, and urban planning. Green Sentry is an AI-powered hyper local weather prediction and alert system designed to overcome these limitations by leveraging machine learning, spatiotemporal analytics, and climate datasets. The system predicts precipitation, classifies weather risks, and triggers alerts in real time. Green Sentry integrates LSTM-based time-series modeling, ensemble machine learning for anomaly detection, GIS-based visual mapping, and a web interface that delivers localized in sights at street-level granularity. Evaluated using datasets from Open-Meteo API, World Bank CCKP, and regional weather logs, the system achieves an MAE of 3.1mm, an RMSE of 5.2 mm, and a heavy rainfall prediction accuracy of 90.1%. Experimental results demonstrate improvements in prediction precision, response time, and contextual climate awareness compared to baseline models. The proposed system supports decision-making in agriculture, flood management, irrigation planning, transportation, and community safety. This paper presents the system architecture, model implementation, evaluation, limitations, and future enhancements toward climate-resilient, AI-driven local forecasting tools.

1. INTRODUCTION

Weather prediction is an essential component of modern environmental planning, agriculture, transportation, and disaster response. As climate patterns shift globally, extreme weather events such as floods, heat waves, and unseasonal rainfall have become more frequent. These unpredictable changes intensify the need for high-accuracy, localized (hyper local) weather predictions that can support real-time decision-making. Traditional weather applications rely on numerical weather prediction (NWP) models, which use large-scale physical simulations. Although effective for regional forecasting, NWP models provide coarse spatial resolutions and often struggle with micro climatic variations influenced by terrain, urban structures, and water bodies. To address these challenges, AI-driven approaches have gained popularity due to their ability to learn complex temporal and spatial patterns from large datasets. Deep learning models such as LSTM (Long Short-Term Memory), CNN (Convolutional Neural Networks), and hybrid transformer-based time-series models have demonstrated strong predictive capabilities for rainfall, temperature, humidity, and wind patterns.

Motivation for Hyper local forecasting hyper local forecasts offer street level accuracy, enabling:

- Precision agriculture (irrigation timing, fertilizer planning)
- Flood prevention and storm-water management
- Smart city resource allocation
- Transportation route optimization
- Emergency alerting for vulnerable communities However, current systems rarely combine:

1. Climate projections
2. Local sensor data
3. Real-time machine learning inference
4. Interactive user interfaces with actionable alerts

Green Sentry aims to fill this gap by providing a complete AI-powered hyper local weather prediction ecosystem.

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Objectives

The major research objectives of Green Sentry are:

1. To build a real-time model that predicts next-day rainfall with high accuracy.
2. To implement hyper local mapping using GIS and location-based queries.
3. To integrate ensemble ML models for improved anomaly and extreme-event detection.

II. LITERATURE SURVEY

Weather forecasting has evolved from traditional statistical models to advanced AI-based approaches. This section discusses existing research contributions and how they shaped the design of Green Sentry.

Traditional Weather Prediction Models Early forecasting relied heavily on:

- Numerical Weather Prediction (NWP)
- Statistical time-series methods (ARIMA, regression)
- Satellite and radar observations

While useful for broad-scale predictions, these models:

- Lack fine-grained accuracy
- Require high computational resources
- Perform poorly in rapidly changing local conditions

Deep Learning for Weather Prediction Recent advancements include:

- LSTM networks for long-term sequential weather patterns
- CNNs for spatial climate image analysis
- Hybrid models combining spatial and temporal predictions

Shietal.(2020) explored precipitation prediction using deep learning and reported improved accuracy compared to classical meteorological models.

Climate Modeling and Global Datasets

Organizations like World Bank CCKP and NASA provide open-access datasets for:

- Temperature variations
- Rainfall patterns
- Climate risk assessments

These datasets help refine long-term projections and train robust ML models.

Existing Weather Systems Common tools:

- Accu Weather
- Open-Meteo
- Weather API

Google Weather Limitations include:

- Lack of hyper local predictions
- Limited AI-based risk scoring
- Insufficient climate adaptation features

Research Gaps Identified

From the literature, the following gaps persist:

1. Limited integration of climate projection data with real-time forecasting.
2. In sufficient models for detecting extreme weather anomalies.
3. Lack of interactive, user-friendly analytic dashboards.
4. Minimal AI-triggered alert mechanisms.

Green Sentry addresses these gaps through a robust, modular, AI-driven framework.

2. EXISTING SYSTEM

Existing weather prediction systems depend mostly on satellite data, humidity/rain sensors, and regional forecast models. They provide:

- Hourly or daily weather conditions
- Probability of precipitation
- General city-level predictions

1. Limitations
2. No hyper local granularity predictions often cover 5–20 km zones.
3. No machine-learning based real-time risk scoring.
4. Static or non-adaptive predictions that fail under sudden climatic shifts.
5. Lack of integration with climate-change parameters.

These limitations significantly affect sectors requiring high precision, like farming, logistics, and urban planning.

3. PROPOSED SYSTEM – GREEN SENTRY

Green Sentry is designed as a complete hyper local weather prediction and alert ecosystem.

A. System Overview The system integrates:

- Historical weather datasets
- Reanalysis climate datasets
- Open-Meteo API real-time data
- LSTM and ensemble machine-learning models
- Flask-based prediction API
- React-based interactive UI Green Sentry provides:
- Precipitation prediction
- Real-time risk scoring
- 24-hour and 7-day forecast summaries
- Anomaly detection
- Alert recommendation engine

B. Methodology

1. Data Collection:

Data is gathered from Open-Meteo,World Bank CCKP, and regional logs.

2. Preprocessing:

o Normalization
o Missing value imputation
o Outlier detection
o Feature engineering

3. Modeling:

o LSTM model for next-day precipitation
o Ensemble ML (Random Forest+XG Boost) for anomaly detection
o Statistical models for uncertainty estimation

4. Prediction:

Real-time user queries retrieve forecasts via Flask API.

5. Visualization:

o Leaflet.jsmap
o Rain risk score indicator
o Color-coded climate alerts

C. Architecture Diagram

(As described in PPT, rewritten in IEEE style.) Modules:

- Data Ingestion Module
- Preprocessing Engine
- ML Training Component
- Prediction API
- Alert Engine
- Front end Dashboard

4. SYSTEM ARCHITECTURE

The architecture includes three key layers:

A. Data Layer Sources:

- Open-Meteo
- Climate Knowledge Portal
- CSV-based local logs Functions:
- Storage
- Updating
- Cleaning

B. Processing Layer Contains:

- ML models
- Feature extraction pipeline
- Climate anomaly detector
- API inference engine Ensures:
- Low-latency predictions
- Reliable extreme-event detection

C. Application Layer Includes:

- Frontend UI
- Interactive weather map
- Real-time alert panel

This layer provides communication between the user and the prediction engine.

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5. IMPLEMENTATION

A. Technology Stack

- Backend: Python, Flask, Tensor Flow/ Keras
- Front end: React, Type Script,Tailwind CSS
- Data Processing: Pandas, NumPy,Scikit-learn
- Mapping: Leaflet.js
- Deployment: Waitress server, Cloud hosting

B. LSTM Model Architecture

- Input:30-daywindowsoftemperature, rainfall, humidity
- Two stacked LSTM layers
- Dense output layer for rainfall (mm)
- Optimizer: Adam
- Loss: MAE

C. Ensemble Anomaly Detection

Random Forest+ XG Boost identifies:

- Extreme rainfall
- Heat spikes
- Unusual dryness

D. Web Interface Features

- Interactive map
- Risk scale (0–100)
- Fore cast graphs
- Downloadable reports
- Real-time alerts

6. RESULTS AND DISCUSSION

A. Model Performance Metric	Value
MAE	3.1 mm
RMSE	5.2 mm
Heavy Rain Accuracy	90.1% Anomaly detection accuracy 87%

B. Visualization Outputs

- Risk bar chart
- Rainfall trend graph
- Location-based precipitation markers

C. Key Findings

- LSTM significantly outperformed ARIMA baseline.
- Ensemble models improved risk classification.
- Hyper local granularity improved predictions for urban and agricultural areas.

D. Challenges

- Data scarcity in rural regions
- High variability in monsoon seasons
- Sensor inconsistencies

7. CONCLUSION

Green Sentry presents a highly effective AI-powered approach to hyper local weather forecasting. By combining LSTM networks, ensemble ML, and climate datasets, the system demonstrates strong predictive accuracy and real-world applicability. The integration of an intelligent alert system further strengthens its utility in agriculture, transportation, and disaster mitigation. Green Sentry's modular architecture ensures scalability, extensibility, and adaptability to new regions and climatic conditions.

IX. FUTURE ENHANCEMENT

Future improvements include:

- Adding transformer-based time-series forecasting models
- Expanding support to low-resource climatic regions
- Introducing offline prediction capabilities
- Integrating IoT sensors for real-time ground data
- Providing voice-based fore cast services
- Enhancing predictions using satellite imagery (CNN processing)

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