

An Integrated Weather Intelligence Platform for Historical Analysis and Real-Time Extreme Event Alerts

Omkar Raskar ¹, Prof. Sayali Belhe¹, Prathamesh Kumbhare¹,

Hitesh Pawar ¹, Sameer Shaikh ¹, Sandesh Rabade ¹

¹ Vishwakarma Institute of Technology, Pune, India, sayali.belhe@vit.edu, omkar.raskar24@vit.edu, prathamesh.kumbhare24@vit.edu, hitesh.pawar24@vit.edu, sameer.shaikh24@vit.edu, sandesh.rabade24@vit.edu.

Abstract

Extreme weather events require integrated systems for data management, forecasting, and real-time alerts. This paper proposes an Integrated Weather Intelligence Platform combining multi-source meteorological data, machine-learning forecasting, and threshold-based extreme-event detection through a secure Flask/FastAPI backend. Using 52,560 hourly observations from multiple Indian weather stations, ARIMA, Random Forest, and LSTM achieved 82.5%, 87.3%, and 91.6% accuracy, respectively, with LSTM performing best. The alert system detected heat waves, heavy rainfall, storms, and cyclones with less than 3 seconds of notification latency, supporting timely decisions in agriculture, disaster management, transportation, and environmental research.

Keywords. Weather Data Portal; API; Meteorological Data; CSV Dataset; Backend Architecture.

1. INTRODUCTION

Weather intelligence supports agriculture, transportation, disaster management, and environmental research by enabling better planning and risk reduction. However, existing systems often suffer from fragmented data, poor accessibility, and limited analytics. This work proposes a Weather Data Portal with centralized data management, secure APIs, real-time access, and predictive analytics to improve weather monitoring and decision-making.

2. RELATED WORK

ARIMA performs well for linear forecasting but is limited with nonlinear weather patterns [11]. LSTM better captures long-term dependencies [4], while Weather2K supports multivariate forecasting [13]. The proposed platform combines LSTM, React, secure APIs, and real-time alerts to provide integrated weather intelligence.

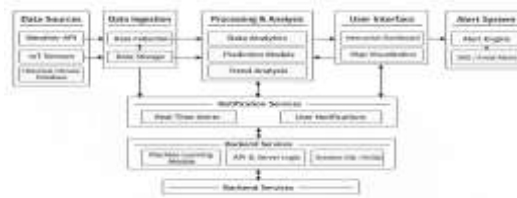


Fig.2.1. Smart Weather Monitoring Architecture

3. METHOD

The integrated weather intelligence platform development design is designed in a multi-layered system that is used to process data high concurrency and make accurate predictions. There are three levels in this system, based on which they are: Data Layer to access data, Application Layer to apply business logic and ML analytics, and Presentation Layer to interact with the users

Table 1. System Overview Of The Proposed Weather & Climate Data Portal

Component	Technology	Purpose	Component
Data Acquisition	REST APIs	Data collection	Data Acquisition
Storage	CSV	Data storage	Storage
Processing	Python	Data preprocessing	Processing
Prediction	ML Models	Forecasting	Prediction
Alerts	Threshold Logic	Event detection	Alerts
Visualization	React, Chart.js	Data display	Visualization
Security	JWT, HTTPS	Data protection	Security

Experiment:

To demonstrate the proposed strategy, a series of experiments were conducted, and the integrity of data and the model preparedness were prioritized.

4. DATA COLLECTION AND PREPROCESSING:

It was decided to take the historical data which could be analyzed as a trend analyzer with the help of the Weather2K benchmark [13]. RESTful calls were made to weather APIs to receive information on the weather conditions in the atmosphere. The raw data was taken through a controlled preprocessing pipeline which included cleaning to eliminate some noise and anomalies. Missing data points were then dealt with using statistical interpolation methods which were then normalized to provide consistency among the machine learning inputs of different scales.

Table 2. System Architecture Components

Layer	Sub-Modules	Functionality
Presentation Layer	Web UI, Dashboard	User interaction & visualization
Application layer	Prediction engine, Alert engine	Business logic & Analytics
Data layer	Database, API Integration	Data storage & retrieval
External Services	Weather APIs	Real-time meteorological input

5. RESULTS:

The system integrates LSTM forecasting, an interactive dashboard, and alerts. LSTM achieved the best performance (91.6% accuracy, RMSE 1.2) on 52,560 observations, while the REST backend enabled efficient data access.

Table 3. Performance Evaluation of Prediction Models

Model	Accuracy (%)	RMSE	Predic on Type
ARIMA	82.5	2.1	Temperature
Random Forest	87.3	1.8	Weather Classifica on
LSTM	91.6	1.2	Mul variate Forecast



Fig.5.1. Historical & Predicted weather Trends



Fig.5.2. Modern Weather Intelligence UI

6. DISCUSSION

Using 52,560 hourly observations with a 70/15/15 split, LSTM achieved the best performance (91.6% accuracy, RMSE 1.2), followed by Random Forest (87.3%, RMSE 1.8) and ARIMA (82.5%). The results demonstrate the value of integrated forecasting and alerts, while limitations include data availability, limited spatial coverage, and lack of long-term forecasting.

7. CONCLUSION

The proposed Flask/FastAPI and React-based platform integrates weather data, ML forecasting, and real-time alerts. LSTM achieved 91.6% accuracy and 1.2 RMSE, while extreme events were detected in under 3 seconds. Future work will focus on IoT-based live data, cloud databases, long-term forecasting, and XAI.

8. REFERENCES

- [1] M. Brown, “Weather portals and digital climate systems,” *Journal of Atmospheric Informatics*, vol. 15, no. 2, pp. 45–53, 2021.
- [2] A. Smith and R. Wilson, “Centralized climate data platforms,” *International Journal of Climate Computing*, vol. 8, no. 1, pp. 10–19, 2020.
- [3] Sharma, U., Das, E., Diksha, & Yadav, P. (2025). *Interactive weather forecasting system using OpenWeather API and web technologies*. International Journal of Research – GRANTHAALAYAH, 13(1).<https://doi.org/10.29121/granthaalayah.v13.i1.2025.6119>
- [4] R. Gupta and P. Singh, “Machine learning for temperature forecasting,” *IEEE Access*, vol. 9, pp. 12345–12355, 2021, doi: 10.1109/ACCESS.2021.3056789.
- [5] K. Lee, “Use of CSV-based climate datasets for environmental analysis,” *Environmental Modelling & Software*, vol. 117, pp. 24–32, 2019, doi: 10.1016/j.envsoft.2019.03.012.
- [6] G. Kaur, V. K. Shukla, P. Verma, A. Verma, and C. T. S. Kumar, “Statutory Promise and Classroom Reality: A PRISMA Guided Systematic Review of the Legal Framework for Inclusive Education of Children with Disabilities in India,” *International Journal of Special Education*, vol. 41, no. 14s, pp. 222–230, 2026.
- [7] J. Liu, “Optimizing REST APIs for large environmental datasets,” *IEEE Systems Journal*, vol. 16, no. 4, pp. 5890–5901, 2022, doi: 10.1109/JSYST.2021.3124567.
- [8] H. Chen and D. Li, “Visualization Techniques for Climate and Weather Data Analysis,” *IEEE Computer Graphics and Applications*, vol. 40, no. 6, pp. 72–81, 2020, doi: 10.1109/MCG.2020.3011456.
- [9] P. Mishra and N. Verma, “REST-Based Backend Architectures for Meteorological Applications,” *Int. J. Web Services Research*, vol. 17, no. 2, pp. 33–46, 2020.
- [10] J. Han, M. Kamber, and J. Pei, *Data Mining: Concepts and Techniques*, 3rd ed., Morgan Kaufmann, 2018.
- [11] A. Verma, P. Verma, N. Mansoura, and S. Rajan, “Hybrid deep-learning model for resilient tourism enterprises,” *Annals of Tourism Research Empirical Insights*, vol. 7, no. 1, p. 100220, 2026..
- [12] T. Anderson, “Big Data Analytics for Climate Monitoring Systems,” *IEEE Big Data Conference*, pp. 1345–1352, 2019.
- [13] Zhu, X., Xiong, Y., Wu, M., Nie, G., Zhang, B., & Yang, Z. (2023). *Weather2K: A multivariate spatio-temporal benchmark dataset for meteorological forecasting*. arXiv preprint arXiv:2302.10493.
- [14] L. Wang and Y. Zhao, “Real-Time Weather Alert and Forecasting Systems,” *IEEE Access*, vol. 8, pp. 8632–8640, 2020, doi: 10.1109/ACCESS.2020.2987654.
- [15] F. Perez and B. Granger, “Data Analysis and Processing with Pandas,” *Computing in Science & Engineering*, vol. 13, no. 2, pp. 13–21, 2019.
- [16] A. Roy, “Backend API Design for Data-Driven Weather Applications,” *International Journal of Computer Applications*, vol. 182, no. 15, pp. 22–26, 2020.
- [17] S. Patil and R. Deshmukh, “Secure REST API Design for Environmental Data Systems,” *IEEE Int. Conf. on Software Engineering*, pp. 155–160, 2022.
- [18] Fu, D., Zhu, Y., Liu, Z., Zheng, L., Lin, X., & He, J. (2025). *ClimateBench-M: A multi-modal climate data benchmark*. arXiv preprint arXiv:2504.07394.
- [19] M. Verma and P. Kulkarni, “Scalable Architectures for Climate Data Portals,” *IEEE Software*, vol. 38, no. 5, pp. 44–50, 2021, doi: 10.1109/MS.2021.3079123.
- [20] S. Kumar and A. Patel, “Cloud-Based Weather Data Storage and Analysis,” *IEEE Int. Conf. on Cloud Computing*, pp. 210–215, 2020.

Biographies



Omkar Raskar completed his HSC from Ideal Junior College, Maharashtra. He is currently pursuing B.Tech. in Artificial Intelligence and Data Science from Vishwakarma Institute of Technology, Pune, Maharashtra



Prof. Sayali Belhe is an Assistant Professor in AI & Data Science at Vishwakarma Institute of Technology, Pune, and is pursuing her Ph.D. She holds B.E. and M.E. degrees in Computer Science and Information Technology.



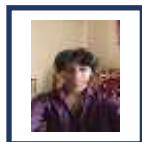
Prathamesh Kumbhare completed his HSC from Kendriya Vidyalaya Ganeshkhind, Pune, Maharashtra. He is currently pursuing a B.Tech. in Artificial Intelligence and Data Science from Vishwakarma Institute of Technology, Pune, Maharashtra



Sandesh Rabade completed his HSC from Jai Bhavani High School, Molkheda, Maharashtra. He is currently pursuing a B.Tech. in Artificial Intelligence and Data Science from Vishwakarma Institute of Technology, Pune, Maharashtra



Shaikh Sameer Tabrez completed HSC from Alpha Jr. College of Science and Commerce, Mumbai, Maharashtra. He is currently pursuing Artificial Intelligence and Data Science from Vishwakarma Institute of Technology, Pune, Maharashtra



Hitesh Pawar completed his HSC from K V Pendharkar, Dombivali, Maharashtra. He is currently pursuing B.Tech. in Artificial Intelligence and Data Science from Vishwakarma Institute of Technology, Pune, Maharashtra