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Smart Umbrella Reminder System Using AI and Iot: A Review Of Context-Aware Weather Alerts, Proximity Tracking And Low-Power Design

Bhor Anwit Rajendra; Prof. M. A. Auti; Prof. M. C. Kolse; Prof. S. K. Said
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, India;

Abstract—Sudden rain and intense sunlight affect daily commuting, yet people frequently leave home without an umbrella or forget it at offices, buses and shops. Conventional umbrellas offer protection but no intelligence. This paper reviews the design of a smart umbrella reminder system that combines Internet of Things (IoT) sensing, wireless proximity tracking and machine-learning-based weather prediction to remind users at the right moment. The review covers environmental sensing of rainfall, temperature, humidity and light; Bluetooth Low Energy (BLE) links between the umbrella and a smartphone for left-behind alerts based on received signal strength; consumption of weather forecasts and short-term precipitation nowcasts; and context-aware logic that considers the user's schedule and location before issuing a reminder. Low-power hardware design, including duty cycling and energy harvesting, is examined because the device must operate for months on a small battery. A layered architecture covering the umbrella node, the smartphone gateway, a cloud service and the user interface is proposed, followed by a research gap analysis, objectives, comparison of connectivity and prediction options, and a discussion of challenges. The review concludes that a low-cost, context-aware smart umbrella is a practical example of how everyday objects can become helpful IoT companions.

Index Terms—Smart umbrella, Internet of Things, Bluetooth Low Energy, weather prediction, context-aware computing, proximity alert, reminder system, low-power design

I. INTRODUCTION

The Internet of Things (IoT) extends network connectivity to everyday objects so that they can sense their surroundings, exchange data and act on it [1]. While large IoT deployments such as smart cities attract most attention, small personal objects offer some of the clearest everyday benefits. The umbrella is a good example: it is needed only occasionally, is easily forgotten and is frequently lost.

Two problems motivate a smart umbrella. The first is leaving home without an umbrella on a day when rain is likely; the second is leaving the umbrella behind after use. Both can be addressed by combining weather information with knowledge of where the umbrella is relative to its owner. In tropical regions such as India, where monsoon showers can begin suddenly, and in summer, when strong sunlight is a health concern, timely reminders have practical value.

This paper reviews the technologies required to build such a system and proposes an architecture that is low-cost, energy-efficient and respectful of user privacy.

II. BACKGROUND AND RELATED WORK

2.1 Context-Aware Computing

Perera *et al.* [2] define context as any information that characterizes the situation of an entity, and context-aware systems adapt their behaviour to that situation. For a smart umbrella, relevant context includes weather now and in the coming hours, the user's location and planned movement, and whether the umbrella is near the user. Fig. 1 classifies the functions of the system.

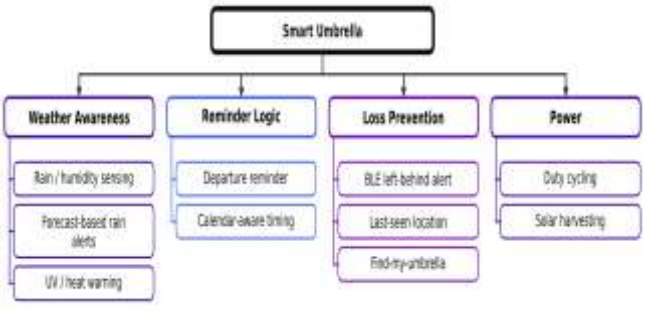


Fig. 1. Functional classification of the smart umbrella system.

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2.2 Wireless Technologies

BLE offers low energy consumption and is supported by almost every smartphone, making it a natural choice for linking the umbrella to its owner [3]. Long-range low-power networks such as LoRaWAN and NB-IoT [4] can locate an umbrella without a phone but require network infrastructure. Lightweight messaging protocols such as MQTT [5] connect the phone or a home gateway to cloud services.

2.3 Review Of Related Studies

Atzori *et al.* [1] and Gubbi *et al.* [6] described the layered structure of IoT systems, separating sensing, networking and application functions; Al-Fuqaha *et al.* [7] reviewed enabling protocols and highlighted energy efficiency as a central constraint for battery-powered nodes. These works form the conceptual basis of any smart personal device.

For proximity detection, Gomez *et al.* [3] evaluated BLE and showed that it can support years of operation on a coin cell for low duty-cycle applications. Faragher and Harle [8] studied BLE beacons for indoor positioning and found that received signal strength (RSSI) fluctuates due to body shadowing and multipath, but that filtering across multiple readings yields useful distance estimates. This directly informs left-behind detection, where the phone must decide whether the umbrella has moved out of range.

Energy is a recurring theme. Sudevalayam and Kulkarni [9] surveyed energy harvesting for sensor nodes and discussed how solar and kinetic sources can extend lifetime when combined with careful duty cycling. A small solar cell on the umbrella canopy is a natural fit.

For predicting rain, Shi *et al.* [10] introduced the convolutional LSTM network for precipitation nowcasting from radar sequences, and Ravuri *et al.* [11] showed that deep generative models produce realistic, skilful nowcasts up to ninety minutes ahead that were preferred by meteorologists. For longer horizons, Pangu-Weather [12] and GraphCast [13] demonstrated that learned models can produce global forecasts competitive with numerical prediction. A smart umbrella does not need to run these models itself; it can consume their outputs through weather services. Table I summarizes the surveyed works.

TABLE I Summary of Literature Survey

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[1]	Atzori et al., 2010	IoT survey and layered vision	Defined sensing, network and application layers	General; no device-level design
[7]	Al-Fuqaha et al., 2015	Survey of IoT protocols	Compared MQTT, CoAP, BLE and others	Energy trade-offs discussed only broadly
[2]	Perera et al., 2014	Context-aware computing for IoT	Lifecycle for acquiring and reasoning on context	No specific personal-device case study
[3]	Gomez et al., 2012	Evaluation of Bluetooth Low Energy	Very low power for low duty-cycle devices	Limited range and throughput
[8]	Faragher and Harle, 2015	BLE beacon fingerprinting	Practical distance estimation with filtering	RSSI unstable near human bodies
[9]	Sudevalayam and Kulkarni, 2011	Survey of energy-harvesting nodes	Solar and kinetic sources extend lifetime	Harvested power is variable
[10]	Shi et al., 2015	Convolutional LSTM nowcasting	Better short-term rain prediction from radar	Requires radar data
[11]	Ravuri et al., 2021	Deep generative radar nowcasting	Skilful, realistic nowcasts preferred by forecasters	High training compute
[12]	Bi et al., 2023	3-D neural network (Pangu-Weather)	Medium-range forecasts rivaling numerical models	Coarse for street-level rain

III. RESEARCH GAP AND OBJECTIVES

3.1 Identified Research Gaps

The following gaps are identified:

- **G1:** Most smart umbrella prototypes rely only on local sensors, which detect rain after it starts rather than predicting it.
- **G2:** Left-behind alerts based on raw RSSI thresholds generate many false alarms in crowded places.
- **G3:** Few designs combine forecasts with the user's calendar and travel time to decide when a reminder is useful.
- **G4:** Battery life and energy harvesting are seldom measured in field use.

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- **G5:** Privacy of continuous location data collected by the companion app is not addressed.

3.2 Objectives Of The Review

The objectives of this review are:

- **O1:** To study IoT sensors, wireless links and power-management techniques suitable for a smart umbrella.
- **O2:** To review machine-learning approaches for short-term rain prediction and proximity estimation.
- **O3:** To propose a layered, context-aware architecture for umbrella reminders and left-behind alerts.
- **O4:** To compare connectivity and prediction options for cost, energy and accuracy.
- **O5:** To identify challenges and future enhancements.

IV. DESIGN OF THE PROPOSED SYSTEM

Fig. 2 presents the proposed architecture. Intelligence is placed mainly on the smartphone and the cloud, keeping the umbrella node simple and energy-efficient.

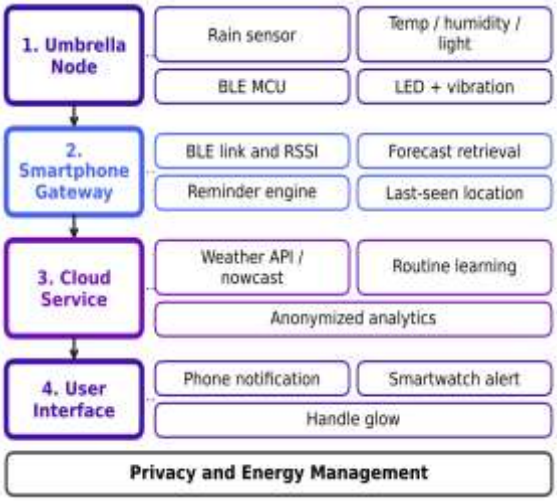


Fig. 2. Proposed layered architecture of the smart umbrella reminder system.

4.1 Umbrella Node

A small module in the handle contains a BLE microcontroller, a rain sensor on the canopy tip, a temperature and humidity sensor, a light sensor, an LED ring and a vibration motor. A small solar cell charges the battery.

4.2 Smartphone Gateway

The companion app maintains the BLE connection, reads sensor data, retrieves forecasts and decides when to remind the user. It also records the last known location where the umbrella was seen.

4.3 Cloud Service

A cloud function combines forecast data with the user's routine to produce rain probabilities for upcoming trips, and stores anonymized usage statistics that help improve reminder timing.

4.4 User Interface

Notifications appear on the phone and smartwatch, and the umbrella handle glows or vibrates when it is needed or when the user walks away from it.

4.5 Methodology

The reminder logic is illustrated in Fig. 3. Before a planned departure, the app estimates the probability of rain along the route during the trip window. A reminder score combines this probability with the importance of the trip and the user's past behaviour:

$$S = w_1 \cdot P(rain) + w_2 \cdot UV + w_3 \cdot H(user) \qquad (1)$$

where P(rain) is the forecast probability of rain, UV is a normalized ultraviolet index for sun protection, and H(user) captures how often the user accepted earlier reminders. A reminder is issued when S exceeds a threshold. For left-behind detection, the distance d is estimated from RSSI with the log-distance path-loss model

$$d = 10^{((P_0 - RSSI) / (10n))} \qquad (2)$$

where P_0 is the RSSI at one metre and n is the environment-dependent path-loss exponent. Readings are smoothed with a moving average, and an alert is raised only when the smoothed distance remains high for several seconds.

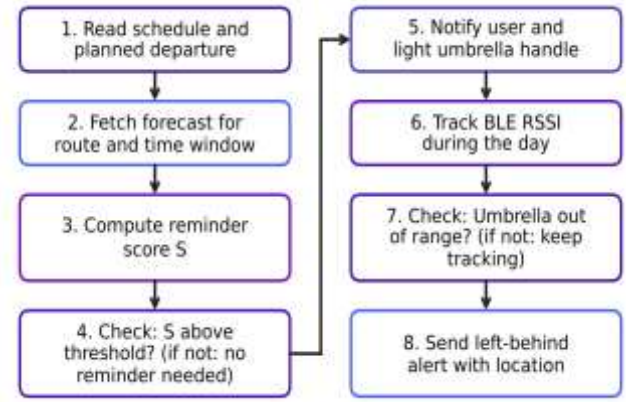


Fig. 3. Reminder and left-behind alert workflow.

V. DISCUSSION AND COMPARISON

Table II compares options for connectivity and prediction. BLE through the phone gives the best balance of cost and energy, while long-range networks allow tracking without a phone at higher cost. For prediction, a weather service is more accurate than local sensing alone.

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TABLE II Comparison of Connectivity and Prediction Options

Option	Cost	Energy	Remarks
BLE via smartphone	Low	Very low	Needs phone nearby
LoRaWAN / NB-IoT	Medium	Low	Tracking without phone; needs network
GPS on umbrella	High	High	Accurate location; short battery life
Local rain sensor only	Low	Low	Detects rain only after it starts
Forecast / nowcast API	Low	None on device	Predicts rain in advance

VI. CHALLENGES AND FUTURE DIRECTIONS

Table III lists the main challenges. Future work may include crowd-sourced rain reports from many umbrellas to improve hyper-local nowcasts, integration with smart-home displays at the doorway, ultra-wideband ranging for precise finding, and tiny on-device models that learn each user's habits without sending data to the cloud.

TABLE III Challenges and Mitigation

Challenge	Mitigation
RSSI false alarms	Smoothing, time windows, motion context
Battery life	BLE advertising intervals, solar cell, sleep modes
Forecast uncertainty	Use probabilities; learn user tolerance
Water ingress	Sealed handle module; waterproof connectors
Location privacy	On-device processing; opt-in sharing

VII. CONCLUSIONS

A smart umbrella reminder system shows how a simple everyday object can benefit from IoT and AI. The reviewed literature provides mature building blocks: low-energy wireless links, practical proximity estimation, energy harvesting and highly skilful learned weather forecasts. By placing computation on the smartphone and cloud, and by combining forecasts with personal context, the umbrella can remind users before rain arrives and alert them before it is lost, while operating for long periods on a small battery.

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