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IoT-Based Smart Technology Modeling for Darunnajah Islamic Boarding School for Plantation Management

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Abstract− Modern plantation management requires an accurate, responsive, and efficient monitoring system to increase crop productivity. The Internet of Things (IoT) is a potential solution for educational institutions such as the Darunnajah Islamic Boarding School, which manages plantations as part of its economic independence. This research aims to develop an IoT technology model based on a layered architecture, encompassing perception, networking, processing, and application layers tailored to the operational context of Islamic boarding schools. Recent literature data was used to formulate sensor requirements, communication protocols, edge-cloud mechanisms, and application designs for students and administrators. The modeling results provide an overview of an IoT implementation that is scalable, energy-efficient, and easily replicated. This study is expected to serve as a technical guide for the development of Smart Islamic Boarding Schools in the plantation sector.

Keywords: IoT, Smart Farming, Smart Islamic Boarding Schools, Plantations, LPWAN

1. INTRODUCTION

The development of Internet of Things (IoT) technology over the past five years has brought about significant changes in modern agricultural management. This technology enables precise agricultural processes through environmental monitoring and more accurate data-driven decision-making. The use of IoT is particularly relevant for plantations managed by educational institutions such as the Darunnajah Islamic Boarding School, as it can increase productivity while providing educational value for students.

The latest generation of IoT sensors can measure temperature, soil moisture, and light intensity stably and energy-efficiently, making them suitable for areas with limited electricity (Soussi et al., 2024). Low-power sensor capabilities are crucial for Islamic boarding school plantations, which cover large areas and require continuous monitoring systems (Mansouri et al., 2023).

Beyond sensors, communication technology is also rapidly evolving. Low-Power Wide-Area Networks (LPWANs) offer longer communication ranges and are resistant to environmental interference, making them ideal for plantations (Arshad et al., 2022). Field testing results show that LPWAN networks are capable of maintaining signal quality in remote agricultural areas (Wu et al., 2021).

In terms of data processing, an edge computing approach allows some analysis to be performed directly on the device, reducing reliance on the cloud (Silva et al., 2021). TinyML technology also enables small devices to run artificial intelligence models to rapidly detect patterns in crop conditions (Lloret et al., 2022).

The implementation of IoT in crop analytics has also been expanded through the use of cameras and deep learning-based plant disease detection models (Kour & Arora, 2021). This approach can improve the accuracy of plant disease identification in field environments (Zhang et al., 2022).

Smart irrigation systems are one of the most relevant implementations for Islamic boarding school plantations. Research shows that sensor-based irrigation automation can increase water efficiency by tens of percent compared to manual methods (Lakhiar et al., 2024). Machine learning-based soil moisture prediction models have also been shown to improve the effectiveness of irrigation scheduling (Lakshmi et al., 2023).

On the other hand, IoT integration in agriculture faces challenges related to data security, requiring a robust protection system (Gong et al., 2025). Another challenge is the difficulty of integrating devices from different vendors, so device interoperability must be planned from the outset (Huang et al., 2023). Data governance is also a critical issue because collected agricultural data must be stored and accessed appropriately (Okafor et al., 2022).

Cloud-edge-based Smart Farming models have demonstrated positive results in increasing data efficiency and accelerating decision-making processes (Abbas et al., 2021). The integration of artificial intelligence technology with IoT also improves the ability to predict crop conditions on a large scale (Su et al., 2023). Low-energy sensors enable IoT to operate for longer periods without human intervention (Ahmed et al., 2020). Renewable energy can also be used as an alternative power source for IoT devices in agricultural areas (Paul et al., 2024).

The IoT approach overall can transform traditional agricultural work patterns into more scalable and efficient ones (Singh et al., 2020). Considering these findings, the development of an IoT technology model on the Darunnajah Islamic Boarding School plantation is crucial to support economic independence while strengthening the digital literacy of students (Verma et al., 2023).

2. RESEARCH METHODOLOGY

This research uses a model engineering method focused on developing an IoT architecture for the Darunnajah Smart Islamic Boarding School, implemented in a plantation area. Model engineering was chosen because it is capable of producing a systematic, structured system design that can be validated through both technical and operational approaches.

2.1 Literature Review

The initial stage of the research was to conduct a systematic literature review of relevant academic publications and industry standards for the 2020–2025 period. The focus of the literature review included:

a. Sensor technology for smart farming, such as soil moisture sensors, soil nutrient sensors, IoT-based mini cameras, and weather sensors.
b. Low Power Wide Area Network (LPWAN) standards such as LoRaWAN and NB-IoT, which have the characteristics of wide coverage and low energy consumption.
c. Edge computing architecture for efficient local data processing in areas with limited infrastructure.
d. Interoperability between IoT devices, including MQTT, CoAP, and HTTP standards for system integration.
e. Implementation model for smart agriculture in educational environments or Islamic boarding school-based communities.

2.2 System Requirements Analysis

The needs analysis was conducted through initial observations and discussions with plantation managers. This stage aims to ensure that the designed IoT system aligns with field characteristics. Aspects analyzed include:

a. Crop Type

Islamic boarding school plantations grow commodities such as oil palm, horticultural vegetables, and fruit trees. Each type requires different measurement parameters, such as soil moisture for vegetables and microclimate conditions for oil palm.

b. Land Structure

Topographic conditions (flat–hilly), soil type (laterite–alluvial), and accessibility level influence the placement of sensors and gateways.

c. Electricity Availability

Some areas have limited electricity access, requiring low-power devices and solar panel support.

d. Distance Between Sensor Points

The network design must ensure that LoRaWAN or NB-IoT can transmit data from sensor points located 1–5 km apart.

e. Management Competence

Ease of operation is a crucial aspect; the system interface must be simple, use Indonesian, and be usable by management personnel without a technical background.

2.3 Layered IoT Architecture Design

The model is built with four layers:

a. Perception Layer: temperature sensors, soil moisture, mini cameras, soil probes.
b. Network Layer: LoRaWAN, NB-IoT, WiFi (for areas near the office).
c. Processing Layer: edge gateway, cloud server, analytics dashboard.
d. Application Layer: web/mobile-based monitoring application.

2.4 Model Validation

Validation is conducted using three approaches:

a. Literature Compliance

Comparing the model to IoT architecture standards in recent research.

b. Evaluation by plantation managers

Discussions to test the feasibility of implementation in the field.

c. Technical Verification

Ensuring each layer meets interoperability and IoT standards.

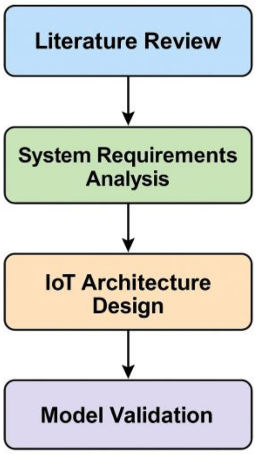

Figure 1. Research Stage

Figure 1 The following is a picture of the research flow that will be carried out at each stage of the research.

3. RESULTS AND DISCUSSION

After several stages, system requirements analysis, and layered IoT architecture design, the resulting model is as follows:

3.1 Perception Layer

Includes sensors for soil moisture, temperature, and light intensity, as well as cameras for disease detection. This layer collects data periodically.

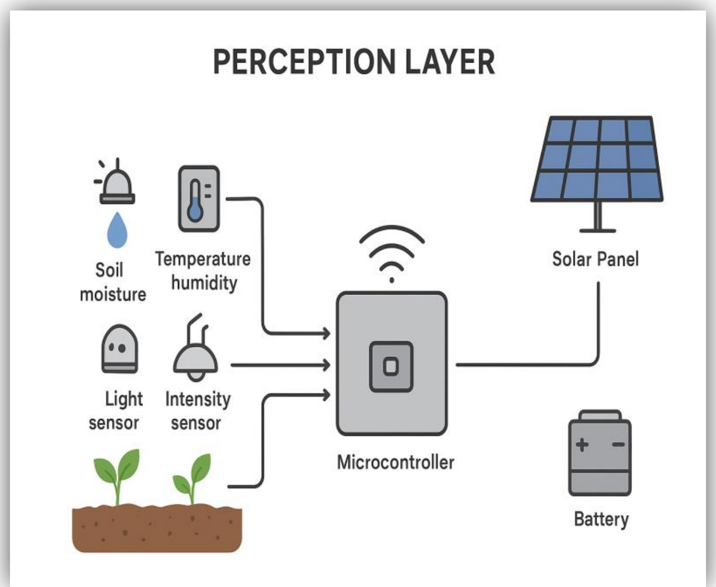

Figure 2. Perception Layer (Data Collection in The Field)

Figure 2 Collect environmental variables and field visuals periodically and reliably.

Main Components:

- Sensors: Soil moisture (capacitive), soil pH/NPK probe (optional), DHT22/DHT33 (temperature & humidity), light sensor (lux/LDR), rain sensor.
- Camera: Low-power IoT camera (e.g., ESP32-CAM) for periodic photos/leaf spot detection.
- Microcontroller node: ESP32 or STM32 (with LoRa/LoRaWAN module or NB-IoT shield).
- Power supply: solar panel + LiFePO4 battery and charge controller (MPPT) for off-grid locations.

Implementation steps (field → device):

1. Site survey: Mark the land block, determine representative points per 0.5–2 ha for sensor node installation (depending on soil heterogeneity).
2. Sensor selection per crop: e.g., vegetables: humidity + pH sensor; oil palm: humidity + microclimate + photo.
3. Casing design & mounting: Use an IP65 casing, mount the humidity sensor at a 1–1.5 m pole and the camera at a 2–3 m pole.
4. Sensor calibration: Perform initial calibration (soil moisture dry/wet points; standard pH).
5. Sampling schedule: Set soil moisture sampling every 30–120 minutes; camera sampling once/three times daily or on-demand.
6. Hygiene & inspection: Clean the camera sensor and lens every month, and check the cables and water protection.

```
[Soil moisture]   [pH probe]   [Temp/Hum sensor]   [IoT-Camera]
      \               |               |                /
              [Mikrokontroler Node (ESP32/LoRa)]
                     (Catu daya: Solar + Bat)
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Figure 3. Image sketch (Perception Layer)

3.2 Network Layer

LoRaWAN is used as the primary network due to its wide coverage and energy efficiency. NB-IoT is considered an alternative if stable operator coverage is available.

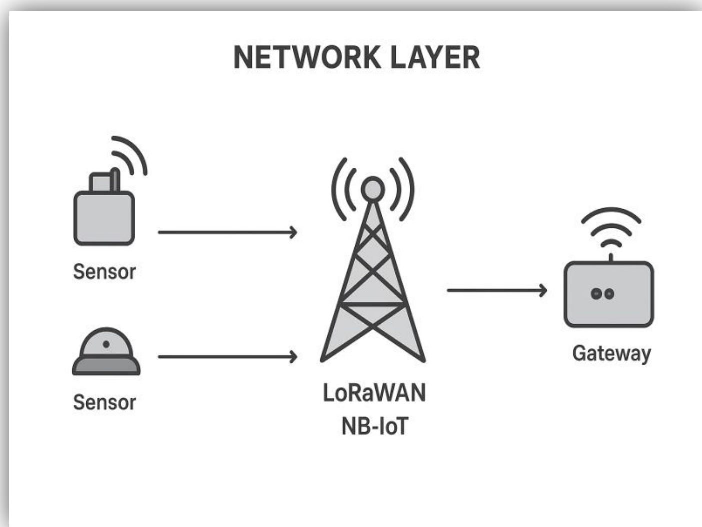

Figure 4. Network Layer (Data Delivery)

Figure 4 Connect field nodes to the gateway/Internet with range and power efficiency.

Main components

- Gateways: LoRaWAN gateways (1–2 units per 100–200 hectares depending on topography); NB-IoT SIMs at the gateway or node; WiFi access points for areas near the office.
- LoRa Server (on-premises or cloud) and Network Server (TTN, ChirpStack, or commercial operator).
- Protocol: LoRaWAN in perception → MQTT or HTTPS from gateway to cloud.

Implementation steps

1. Coverage survey: Test LoRa coverage from potential gateway points (tops of houses, offices, or tall trees).
2. Gateway placement: Place the gateway at the highest point possible, free from obstructions; use external directional antennas if necessary.
3. Backhaul: Connect the gateway to the internet via 4G (USB modem) or a wired connection, if available.

4. Network configuration: Set AppEUI/DevEUI/AppKey for LoRa nodes; configure MQTT QoS for sensor topics.
5. Redundancy: Enable NB-IoT as a backup on critical nodes in case LoRa is disrupted.

```
[Node LoRa] --radio--> [LoRa Gateway] --Internet(MQTT/HTTPS)--> [Cloud/Edge Server]
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Figure 5. Data flow (Network Layer)

3.3 Processing Layer

The edge gateway filters and preprocesses data before sending it to the cloud. The cloud runs machine learning analytics to predict water needs, detect diseases, and monitor growth trends.

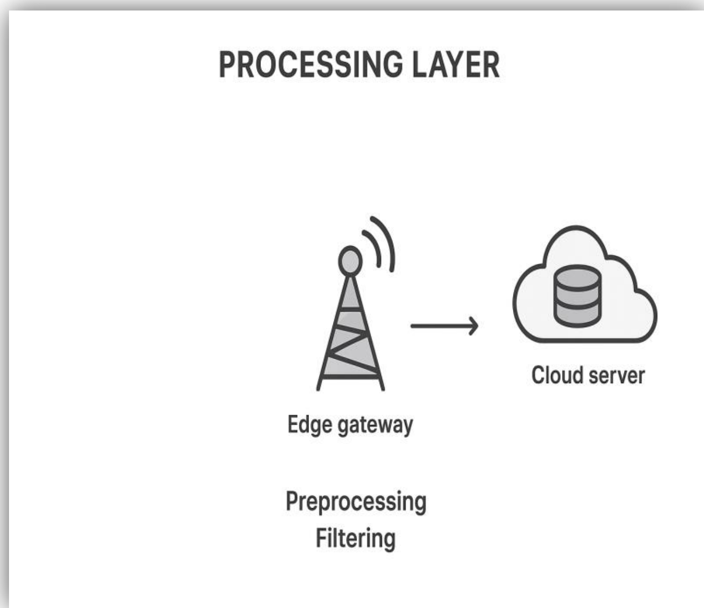

Figure 6. Processing Layer - Processing (Edge & Cloud)

Figure 6 Perform preprocessing at the edge, analytics and storage in the cloud, and ML models for prediction.

Main Components

- Edge Gateway: Raspberry Pi 4 or mini server running a LoRa packet forwarder + edge processing (Node-RED, Python).
- Cloud: VPS or cloud service (DigitalOcean/AWS/Heroku) for the time-series database (InfluxDB), MQTT broker (Mosquitto), and analytics applications (Python, TensorFlow Lite).
- Model: TinyML at the edge for anomaly detection; ML model in the cloud for watering prediction (RF/Gradient Boosting).

Implementation steps

1. Filtering & aggregation at the edge: perform smoothing and outlier removal for noisy sensors.
2. Local rules: implement rule-based alerts at the edge (e.g., moisture < threshold → trigger).
3. Compressed upload: send compact payloads every N minutes; send snapshots on-change or less frequently on a schedule.
4. Model training: collect 1–3 months of data and then train a water need prediction model in the cloud.
5. Model deployment: export the model to TFLite for inference at the edge gateway (for fast response).

[LoRa Gateway] -> [Edge: preprocess, rule engine, TFLite infer] -> [Cloud: DB (Influx), ML train, Dashboard API]

Figure 7. Processing Layer

3.4 Application Layer

The dashboard is used by administrators and students to monitor land conditions in real time, provide moisture graphs, provide early disease warnings, and automatically control irrigation pumps.

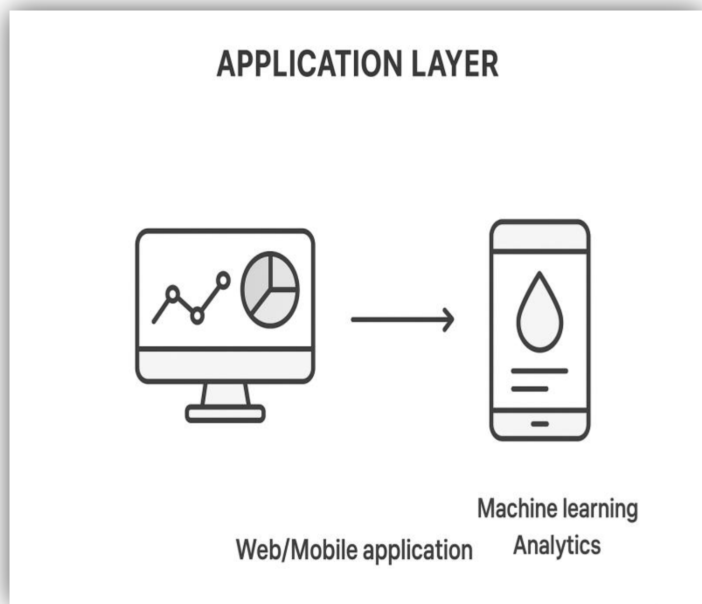

Figure 8. Application Layer (User Interface and Control)

Figure 8 Display data, provide automated/manual control, and documentation for administrators and students.

Main components

- Web dashboard (React/Vue + Node.js/Python Flask backend).
- Lightweight mobile app (Progressive Web App) for real-time notifications (via MQTT over WebSocket / Firebase).
- Control actuators: relay boards that control pumps and valves automatically from dashboard commands or rule engines.

Implementation steps

1. UX design: simple interface: land overview, moisture graph, camera photos, manual pump ON/OFF button.
2. Notification: send SMS/Telegram for critical situations (pump error, very low humidity).
3. Automation scenario: example rule — if soil_moisture < threshold AND predicted_rain = false → start the pump for X minutes.
4. Access & training: create role accounts (admin, operator), conduct a 2-day training session for the manager and several students.

```
[Web Dashboard] <--> [Cloud API / DB]
      |
[Mobile PWA / Telegram Alerts]
      |
[Actuator: Pump Relay / Valve]
```

Figure 9. Sketch (Application Layer)

4. CONCLUSION

IoT modeling for the Darunnajah Smart Islamic Boarding School demonstrates that the integration of sensors, LPWAN, edge computing, and an application dashboard can improve plantation management efficiency. The designed layered architecture supports continuous monitoring, predictive analytics, and automated control. This model can serve as a blueprint for real-world implementation and can be replicated for other Islamic boarding schools or agricultural areas.

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