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# Smart Greenhouse Using Ai And Iot: A Review Of Climate Sensing, Automated Control And Predictive Microclimate Management

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**Abstract—A smart greenhouse is an IoT-based automated agriculture system that maintains suitable conditions for plant growth while reducing water, energy and labour. Conventional greenhouses depend on continuous human monitoring and manual switching of pumps, fans and lights, which wastes resources and allows stress conditions to go unnoticed. This paper reviews AI- and IoT-enabled smart greenhouses. It examines sensing of temperature, humidity, soil moisture, light intensity and carbon dioxide; microcontroller platforms such as Arduino and ESP32 that drive irrigation pumps, exhaust fans, foggers and grow lights; and communication through Wi-Fi and MQTT to cloud dashboards and mobile applications for remote monitoring. Beyond fixed-threshold control, it reviews machine learning that predicts the greenhouse microclimate a few hours ahead, recurrent networks for time-series forecasting, and AI-based climate and irrigation strategies that have competed with expert growers. A five-layer architecture comprising sensing, edge control, connectivity, cloud intelligence and user application is proposed, along with research gaps, objectives, a comparison of control strategies and challenges such as sensor drift, power failures, energy cost and crop-specific tuning. The review concludes that predictive, AI-assisted control can make greenhouses more productive and resource-efficient than threshold-based automation alone.**

**Index Terms—Smart greenhouse, IoT, ESP32, climate control, soil moisture, LSTM forecasting, precision agriculture, controlled environment agriculture**

## I. INTRODUCTION

A greenhouse protects crops from weather, pests and seasonal limits, but only if its internal climate is kept within a narrow band. On a sunny afternoon the temperature inside can rise by more than ten degrees in an hour, and a few hours of heat or water stress can damage flowers or fruit. Manual control cannot react at this speed, especially when the farmer is away.

Shamshiri *et al.* [1] reviewed greenhouse automation and controlled environment agriculture and described the transition from simple on–off control towards plant factories with integrated sensing, actuation and optimization. Low-cost IoT hardware now makes such automation accessible to small growers [2].

This paper reviews sensing, control and AI methods for smart greenhouses and proposes a predictive, layered architecture.

## II. BACKGROUND AND FUNDAMENTAL CONCEPTS

### 1. Greenhouse Climate Variables

Fig. 1 groups the controlled variables into air climate (temperature, humidity, $CO_2$), root zone (soil moisture, nutrients), light (intensity, photoperiod) and energy use. These variables interact: ventilation lowers temperature but also humidity and $CO_2$.

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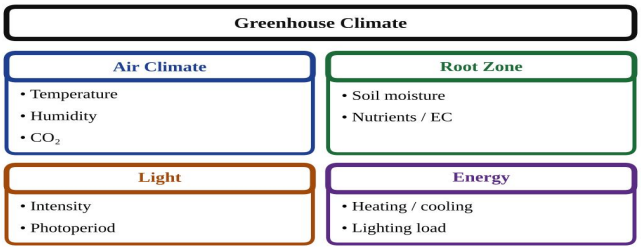



Fig. 1. Controlled variables in a smart greenhouse.

### 2. Control Strategies

Threshold control switches an actuator when a variable crosses a set point. Predictive control uses a model of the greenhouse to anticipate future conditions and act early, which reduces overshoot and energy use [3].

## III. LITERATURE SURVEY

Tzounis *et al.* [2] surveyed IoT in agriculture and identified greenhouses as one of the most mature application areas, while noting challenges of interoperability, power supply and data management. Gubbi *et al.* [4] described the IoT vision and architectural elements on which such systems are built, and MQTT [5] is widely used for lightweight sensor-to-cloud messaging.

Goap *et al.* [6] combined soil-moisture sensing with weather forecasts and machine learning to schedule irrigation, showing water savings over fixed schedules. Liakos *et al.* [7] reviewed machine learning in agriculture and highlighted water and crop management tasks suited to greenhouses. Recurrent networks such as LSTM [8] are suitable for forecasting temperature and humidity from past sensor readings.

Hemming *et al.* [9] reported an international challenge in which AI teams remotely controlled the climate and irrigation of cucumber greenhouses; several AI strategies achieved yields comparable to or better than an expert-grower reference while using resources efficiently. Iddio *et al.* [3] reviewed energy-efficient greenhouse operation and modelling, emphasizing that heating, cooling and lighting dominate costs. Table @lit summarizes these works.

| Ref. | Author(s) / Year | Technique / Approach | Key Contribution | Limitation / Gap |
|---|---|---|---|---|
| [4] | Gubbi et al., 2013 | IoT vision and architecture | Layered IoT framework | Generic, not crop-specific |
| [2] | Tzounis et al., 2017 | Survey of IoT in agriculture | Greenhouse as mature use case | Review only |
| [1] | Shamshiri et al., 2018 | Review of greenhouse automation | Path to plant factories | Limited AI focus |
| [6] | Goap et al., 2018 | IoT + ML irrigation | Forecast-based water saving | Open field setting |
| [7] | Liakos et al., 2018 | Review of ML in agriculture | Mapped ML tasks | Review only |
| [9] | Hemming et al., 2019 | AI remote greenhouse control | AI matched expert growers | High-tech greenhouses |
| [3] | Iddio et al., 2020 | Greenhouse energy review | Energy modelling and control | Few low-cost systems |

TABLE I Summary of Literature Survey

## IV. RESEARCH GAP

- Most low-cost systems use fixed thresholds and react only after conditions drift.
- Coupling between temperature, humidity and $CO_2$ is rarely handled jointly.
- Crop-stage-specific set points are seldom adapted automatically.
- Energy consumption is not optimized alongside crop conditions.

- Systems often stop working during internet or power outages.

## V. OBJECTIVES

- To review sensing and actuation hardware for smart greenhouses.
- To compare threshold, rule-based and predictive control strategies.
- To examine machine learning for microclimate forecasting.
- To propose a five-layer predictive smart greenhouse architecture.
- To identify challenges and future enhancements.

## VI. PROPOSED SYSTEM ARCHITECTURE

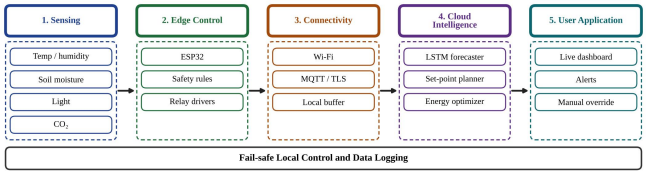



Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer predictive smart greenhouse architecture.

### 1. Sensing Layer

DHT22 or SHT31 sensors measure air temperature and humidity, capacitive probes measure soil moisture, an LDR or BH1750 measures light, and an NDIR sensor measures $CO_2$.

### 2. Edge Control Layer

An ESP32 reads sensors every minute, applies safety rules locally and switches relays for the pump, exhaust fan, fogger and grow lights, so the greenhouse keeps running without internet.

### 3. Connectivity Layer

Readings and actuator states are published over Wi-Fi using MQTT with TLS; data are buffered locally during outages.

### 4. Cloud Intelligence Layer

An LSTM model forecasts temperature and humidity for the next few hours; a planner adjusts set points by crop stage and pre-cools or pre-ventilates before predicted peaks.

### 5. User Application Layer

A mobile dashboard shows live conditions, history and alerts and allows manual override.

## VII. METHODOLOGY AND WORKING

Fig. 3 describes the control cycle. The forecaster predicts the next temperature from a window of past readings,

$$\hat{T}_{t+h} = f_LSTM(x_{t-k}, \ldots, x_t) \quad (1)$$

and the fan is activated early when the forecast exceeds the upper limit. The planner chooses actions that minimize

$$J = \Sigma\,(w_1 \cdot |T - T^*| + w_2 \cdot |RH - RH^*| + w_3 \cdot E) \quad (2)$$

where T *and RH* are crop-stage targets and E is actuator energy.

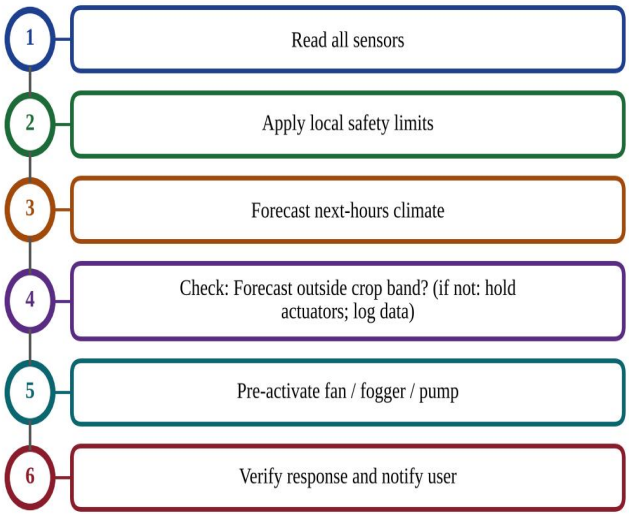



Fig. 3. Predictive greenhouse control cycle.

## VIII. COMPARATIVE ANALYSIS

Table II compares control strategies. Threshold control is simple and robust, fuzzy rules handle interacting variables smoothly, and predictive or AI-based control reduces stress and energy use at the cost of modelling effort.

| Strategy | Complexity | Handles Coupling | Energy Efficiency |
|---|---|---|---|
| Fixed threshold | Low | No | Low |
| Timer schedule | Low | No | Low–Medium |

| Strategy | Complexity | Handles Coupling | Energy Efficiency |
|---|---|---|---|
| Fuzzy rules | Medium | Partly | Medium |
| ML forecast + rules | Medium | Yes | High |
| Model predictive / RL | High | Yes | High |

TABLE II Comparison of Greenhouse Control Strategies

## IX. CHALLENGES AND FUTURE SCOPE

Table III summarizes challenges. Future directions include camera-based plant growth and disease monitoring, solar-powered nodes, reinforcement learning for climate control and digital twins of the greenhouse.

| Challenge | Mitigation |
|---|---|
| Sensor drift / humidity damage | Periodic calibration; protected housings |
| Power or internet failure | Local rules; battery and data buffer |
| Crop-specific set points | Stage-wise profiles; grower feedback |
| Energy cost | Predictive pre-cooling; solar supply |
| Farmer skill | Simple app in local language |

TABLE III Challenges and Mitigation

## X. CONCLUSION

Smart greenhouses combine IoT sensing, microcontroller-based actuation and remote monitoring to keep crops in optimal conditions with less labour. The reviewed literature shows that predictive and AI-assisted control can match expert growers while conserving water and energy. A layered design with local fail-safe control and cloud-based forecasting offers a practical path for farmers to adopt intelligent greenhouse management.

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