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Study on Light Response Mechanism and Yield Prediction of Tropical Dragon Fruit Integrating Multimodal Data and Machine Learning

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Abstract: In off-season dragon fruit cultivation in Hainan, artificial supplementary lighting has become a critical method for improving winter flowering rates. However, current lighting management predominantly relies on empirical approaches, resulting in suboptimal parameters, high energy consumption, and unstable yields. To address these challenges, this study proposes a research framework integrating multimodal data and machine learning to elucidate light response mechanisms in dragon fruit and achieve precise yield prediction. The study first establishes a multimodal dataset incorporating environmental conditions, image data, and physiological indicators through field orthogonal experiments. Next, interpretable machine learning algorithms are employed to quantify nonlinear relationships between lighting parameters and flowering rates, enabling optimal lighting strategies. Subsequently, YOLO object detection combined with LSTM/Transformer time-series models facilitates automated flower-fruit tracking and dynamic yield prediction. Finally, an integrated intelligent lighting decision support system prototype is developed. This research aims to transition from experience-driven approaches to data-driven intelligent solutions, providing theoretical foundations and technical references for precision cultivation of tropical fruit trees.

Keywords: Pitaya; Multimodal data; Machine learning; Light response mechanism; Yield prediction; Intelligent supplementary lighting

1. Introduction

Leveraging its unique tropical light and temperature advantages, Hainan has become China's only province capable of achieving year-round pitaya fruit supply. Off-season pitayas (from November to April of the following year) enjoy significant price competitiveness in winter-spring markets, forming the core of industrial differentiation strategies. However, insufficient natural daylight during winter results in low flowering rates and irregular blooming patterns, creating a critical bottleneck that constrains off-season cultivation yields[1]. Currently, farmers predominantly employ nighttime lighting technology to compensate for inadequate sunlight exposure. Yet lighting methods (including duration and rhythm) often rely on subjective experience rather than scientific principles, leading to energy waste and inconsistent outcomes.

Current research predominantly focuses on the impact of single light factors (such as light quality and duration) on flower formation in dragon fruit [2,3], yet studies on the synergistic effects of multidimensional parameters like supplementary lighting and light-off schedules under Hainan's specific climate remain insufficient. Meanwhile, traditional yield estimation relies on manual experience, lacking temporal perception and predictive capabilities for growth dynamics. With the rapid advancement of IoT, machine vision, and deep learning technologies, multi-source data fusion and intelligent decision-making have demonstrated significant potential in facility agriculture [4,5]. However, intelligent systems for off-season supplementary lighting in dragon fruit cultivation remain unexplored.

This study aims to address the aforementioned challenges by proposing an integrated research framework that combines multimodal data and machine learning. By integrating environmental, image, and physiological data, the framework constructs light-response mechanism models and dynamic yield prediction models, ultimately forming an intelligent light supplementation decision support system. This provides novel solutions for precise and intelligent management of non-seasonal cultivation of pitaya.

2. Research Plan and Technical Approach

The overall research approach is data-driven, aiming to establish a closed-loop system of "perception-modeling-decision-making." The study content is divided into four core components, with the technical roadmap illustrated in **Figure 1**.

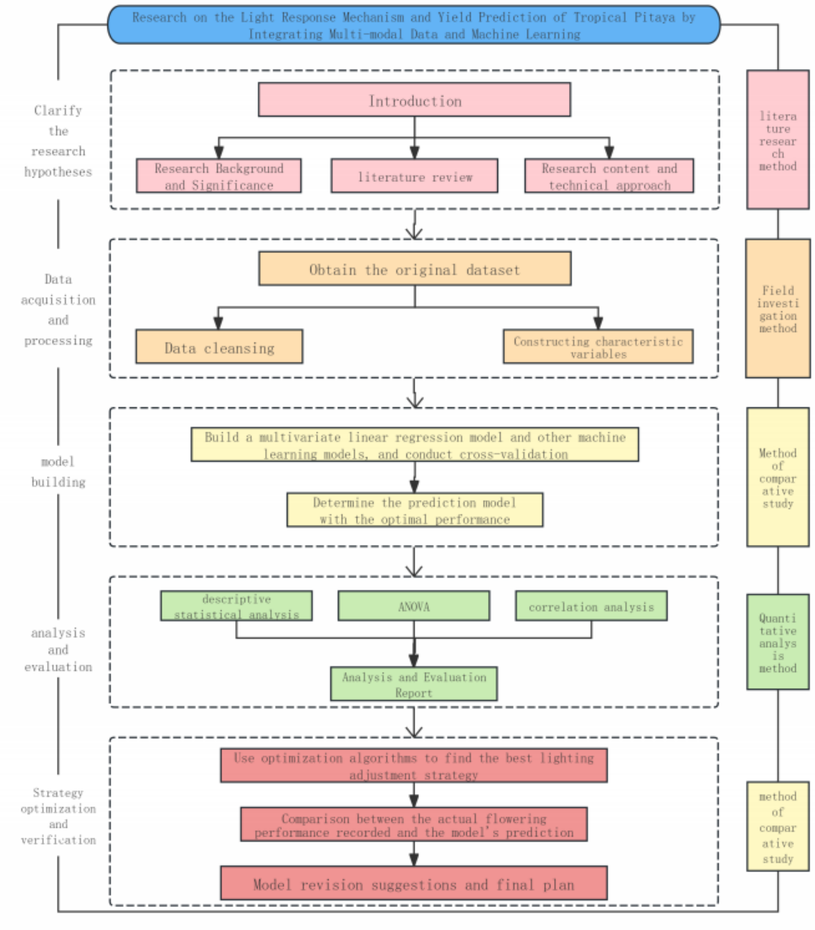

Figure 1. Technical Roadmap of the Research

2.1. Multimodal Data Acquisition and Standardized Dataset Construction

This study employed a pitaya cultivation base in Ledong, Hainan as the experimental site, adopting an orthogonal experimental design to develop various supplementary lighting protocols using incandescent lamps as the unified light source. The research focused on investigating the effects of initial lighting timing, duration, and light-off cycles. Through the deployment of sensor networks, fixed-point cameras, and manual measurements, three types of data were simultaneously collected:

Environmental data: time-series data such as temperature and humidity.

Image data: High-definition canopy images of dragon fruit for recording plant growth status.

Physiological data: key indicators such as bud emergence date, number of flowers, and fruit set rate.

Finally, the aforementioned multi-source heterogeneous data were cleaned, aligned, and standardized to construct a multimodal dataset with unified spatiotemporal benchmarks [6].

2.2. Data-driven modeling of light-responsive mechanisms

This study aims to elucidate the intrinsic relationship between supplementary lighting strategies and physiological responses in dragon fruit. First, variance analysis and regression analysis were employed to identify key drivers influencing flower formation and fruit setting from preprocessed data. Second, interpretable machine learning algorithms such as random forest and gradient boosting decision trees were utilized to construct quantitative relationship models between supplementary lighting parameters (duration and rhythm) and floral/fruit response indicators (flowering rate and fruit setting rate), quantifying their nonlinear response dynamics. Finally, based on this model, sensitivity analysis was conducted to explore optimal supplementary lighting strategies and light-off rhythms [7] under specific light source conditions, with the objectives of maximizing economic benefits or light energy utilization efficiency.

2.3. Construction of Dynamic Production Forecasting Model Incorporating Temporal Sensitivity

This section constitutes the technical core of the project, designed to bridge the gap between static observation and dynamic prediction. First, we employ the YOLOv series object detection algorithms to train deep learning models capable of accurately identifying pitaya flowers, green fruits, and red fruits [8]. By integrating multi-object tracking algorithms, we continuously monitor fruits within image sequences, automatically generating growth temporal curves for each fruit to form a time-series dataset of flower and fruit quantity and size. Second, we combine historical sequence data of flowers and fruits, environmental temporal data, and supplementary lighting records to construct model input features. Finally, utilizing Long Short-Term Memory Networks (LSTM) or Transformers as core architectures, we develop time-series prediction models to achieve rolling forecasts for yield trends, harvesting peaks, and final production volumes over the next 1-4 weeks [9].

2.4. Integration and Validation of the Intelligent Illumination Compensation Decision Support System

This section aims to establish a closed-loop application system for perception, prediction, and decision-making. First, the light response mechanism model and optimal strategies are formalized into computer-readable knowledge rules or quantitative sub-models to construct a decision-making knowledge base. Second, an optimization algorithm is designed to integrate real-time plant status, current environmental data, and short-term weather forecasts, generating customized lighting supplementation plans (including activation timing and duration) for different crop plots with objectives of maximizing economic benefits or light efficiency. Finally, a software prototype system incorporating data dashboards, yield prediction modules, and lighting decision-making modules is developed and deployed at experimental sites. By comparing system-recommended solutions with traditional approaches in terms of yield, quality, and energy consumption, the effectiveness and advantages of this intelligent decision-making system are comprehensively evaluated.

3. Key Issues to be Addressed and Innovations

3.1. Key Issues to be Addressed

(1) Question 1: Light environmental thresholds and circadian rhythms

Under multifactorial coupling, the critical light thresholds and optimal light-dark rhythms for pitaya winter flowering remain unclear. Existing studies focus on single light factors, ignoring nonlinear interactions among lighting initiation timing, duration, and dark intervals, as well as modulation by temperature and humidity. Additionally, photoperiod effects show time lags and cumulative impacts across flowering periods. This study employs orthogonal field experiments combined with explanatory machine learning (random forest, gradient boosting) to construct a nonlinear response surface model. Time-series analysis with lagged variables captures cumulative effects, ultimately identifying optimal light thresholds and dark rhythms that maximize flowering rate and energy efficiency under Hainan's winter conditions.

(2) Question 2: Automated perception of flower/fruit quantities and dynamic yield prediction

Achieving precise, automated recognition of pitaya flowers and fruits in complex field environments and establishing reliable dynamic yield predictions is challenging. Key difficulties include target detection under variable illumination and overlapping plant structures, multi-object tracking across growth stages without individual identification, and fusion of discrete image data with continuous environmental and lighting records. This study applies YOLO-based detectors with Deep SORT for continuous fruit tracking, generating individual growth trajectories. A multimodal LSTM or Transformer network integrates image-derived features (flower/fruit counts and growth rates), environmental time series, and lighting histories to forecast yield trends and final yields 1–4 weeks ahead.

(3) Question 3: From knowledge and data models to intelligent decision-making

Translating models into actionable decisions requires bridging the gap between prediction and optimization. Challenges include integrating deterministic mechanistic rules (e.g., light thresholds) with probabilistic data-driven outputs, balancing multiple objectives (yield, quality, energy consumption, grid load), and adapting to plot-specific variability. This study designs a hierarchical decision engine: a knowledge base encoding optimal circadian rules, and an optimizer using genetic algorithms or particle swarm optimization to generate supplementary lighting schemes under hardware and production constraints. A closed-loop "perception-prediction-decision-execution-feedback" architecture enables adaptive learning, validated through comparative field trials against traditional practices.

3.2. Innovations

(1) Innovation 1: Multimodal data fusion for light response modeling

Traditional pitaya lighting studies rely on single-factor analysis (light quality, intensity, or duration) using ANOVA, ignoring synergistic effects and nonlinear interactions with temperature/humidity. This innovation systematically integrates three heterogeneous data types—sensor-based environmental time series, fixed-camera canopy images, and manual physiological records—into a spatiotemporally aligned multimodal dataset. Orthogonal experiments simultaneously vary lighting start time, duration, and dark intervals. Interpretable machine learning (random forest, gradient boosting) constructs a nonlinear response surface model, quantifying marginal contributions and revealing critical light thresholds and optimal circadian rhythms. This shifts the paradigm from qualitative single-factor analysis to data-driven quantification of nonlinear responses.

(2) Innovation 2: Dynamic temporal perception for yield prediction

Conventional yield estimation uses manual inspection or historical averages, providing static cross-sectional snapshots without tracking individual growth or utilizing temporal dependencies. This innovation integrates YOLOv8 object detection with Deep SORT multi-object tracking to automatically identify and continuously track pitaya flowers, green fruits, and red fruits under complex field conditions (varying illumination, leaf occlusion). Complete growth trajectories from bud to maturity are generated. LSTM or Transformer-based multimodal time series models fuse image-derived features (fruit counts, growth rates), environmental data, and lighting histories, enabling rolling predictions of yield trends, harvest peaks, and final output 1–4 weeks ahead—transforming static estimation into dynamic, proactive forecasting.

(3) Innovation 3: Dual-driven intelligent decision-making (knowledge + data)
Existing systems are either rule-based (rigid, non-adaptive) or pure data-driven black boxes (uninterpretable, lacking physiological grounding). This innovation develops a three-tier hierarchical decision engine: a knowledge layer encoding optimal light thresholds and physiological rules from mechanism models; a data layer providing real-time forecasts and plant status; and an optimization layer using genetic algorithms or particle swarm to balance multiple objectives (yield, quality, energy consumption, equipment constraints). The closed-loop feedback system enables adaptive personalization across plots and climates, and outputs interpretable rationales alongside decisions, bridging the gap from prediction to actionable, farmer-trusted recommendations.

(4) Innovation 4: Research paradigm and demonstration for tropical specialty crops
Most agricultural AI research targets staple or greenhouse crops, leaving tropical specialty crops like pitaya underdeveloped. This study establishes the first systematic “perception-modeling-decision-making” framework for off-season pitaya in Hainan, covering data collection, mechanism modeling, dynamic prediction, and intelligent decision-making. A hardware-software prototype system with dashboards, forecasting modules, and lighting optimization is field-validated against traditional practices, providing quantifiable techno-economic evaluations. Collaborating with local leading enterprises, the project enables rapid translation through training and demonstration bases, offering a replicable paradigm for smart agriculture in other tropical fruits (passion fruit, wax apple) and supporting rural revitalization.

4. Experimental Design

This study employs an orthogonal experimental design ($L_{16}(4^5)$) at a representative pitaya cultivation base in Ledong, Hainan, to investigate light response mechanisms. Three core parameters—supplementary lighting start time, illumination duration, and lamp-off intervals—are systematically varied across 16 treatment combinations with three replicates each. Positive controls follow local farmers’ conventional lighting protocols, while negative controls receive no supplemental light. A multi-modal “space-earth-human” data acquisition system is deployed, integrating meteorological stations, soil sensor networks, fixed cameras (front and overhead angles), drone inspections, manual phenological observations (flowering number, fruit set, quality), and management records (irrigation, fertilization, pruning, lighting status). Environmental parameters (temperature, humidity, light intensity, soil moisture) are logged every 10 minutes and uploaded to a cloud database via 4G/NB-IoT.

Data quality control includes removal of sensor failures and extreme-weather outliers, interpolation for missing values, normalization, and temporal-spatial alignment using a plot-plant-flowering period index. All multi-modal data are stored in HDF5 format. The light response model predicts current flowering rate based on input features such as lighting timing and duration, lamp-off intervals, daily mean temperature and humidity, and a lagged flowering rate from the previous period. Candidate algorithms include Random Forest, GBDT, XGBoost, and LightGBM, with evaluation metrics R^2, RMSE, and MAE. This design enables rigorous validation of the intelligent decision-making system through closed-loop testing.

5. Conclusion

This study addresses scientific challenges and technical bottlenecks in supplementary lighting management for off-season dragon fruit cultivation in Hainan by proposing an intelligent solution integrating multimodal data and machine learning.

Through systematic data collection, mechanism modeling, dynamic prediction, and system integration, the research aims to achieve deep understanding of light response patterns in dragon fruit and refined yield forecasting. The findings not only hold promise for overcoming current manual experience-dependent lighting management models to enhance off-season cultivation yields and profitability, but also provide theoretical foundations and technical paradigms for intelligent production of other tropical fruits and vegetables. These advancements will drive sustainable development of tropical specialty agriculture toward precision and digitalization.

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Disclosure statement

The author declares no conflict of interest.

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