An AI-Integrated Renewable-Powered Cold Storage System with Advanced Environmental Sensing for Smallholder Farmers

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ABSTRACT

Smallholder farmers often face significant post-harvest losses due to the lack of affordable and efficient cold storage infrastructure, which limits their ability to maintain production quality and capitalize on favorable market conditions. Conventional storage systems are energy-intensive, rely on grid power, and lack real-time monitoring or predictive spoilage management. To address these challenges, this study presents an AI-integrated renewable-powered cold storage system equipped with advanced environmental sensing and an edge-based Long Short-Term Memory (LSTM) model for spoilage prediction and freshness assessment. The proposed method combines solar Photovoltaic (PV) energy, Phase Change Material (PCM)-assisted hybrid cooling, multi-sensor environmental monitoring (temperature, humidity, CO_2, ethylene, and NIR spectral sensing), and edge AI-powered freshness indexing to enable proactive quality control and informed market dispatch decisions. Experimental validation demonstrated a 28% reduction in grid energy use, shelf life extension of up to 4×, high spoilage prediction accuracy (RMSE: 0.47 days, MAE: 0.31 days), and a 22% increase in farmer income with a 2.1× RoI over three years. These findings establish the proposed system as a scalable, energy-efficient, and intelligent solution for reducing post-harvest losses and enhancing socio-economic outcomes for smallholder farmers. Future work will focus on scalable AI model enhancements, blockchain-based traceability, and dynamic pricing intelligence to further strengthen system performance and impact.

Keywords-renewable-powered cold storage; edge AI; spoilage prediction; shelf life extension; smallholder farmers; LSTM

I. INTRODUCTION

Post-harvest losses continue to pose significant challenges in agriculture, particularly for smallholder farmers in developing economies, where perishable products often deteriorate before reaching markets. Studies indicate that such losses can reach 30-40% for fruits and vegetables due to insufficient cold storage facilities and inadequate logistics infrastructure [1, 2]. These losses reduce farmer income, create supply chain inefficiencies, and contribute to food insecurity. Conventional cold storage facilities rely heavily on grid electricity and standard vapor compression refrigeration systems, resulting in high energy costs and limited accessibility in rural areas [3]. Although solar-powered cold rooms and Phase Change Material (PCM)-assisted refrigeration have emerged as sustainable alternatives, they primarily focus on temperature stabilization rather than providing real-time environmental intelligence [4, 5].

Similarly, recent IoT-enabled cold storage systems monitor basic environmental parameters such as temperature and humidity, but lack predictive intelligence for spoilage and do not dynamically optimize cooling or ventilation settings [6]. AI-based models for shelf-life prediction have shown promising results for perishable food logistics [7, 8], but are mainly based on cloud-based computation, making them unsuitable for low-bandwidth rural regions where connectivity is not reliable [9]. In [10], a fuzzy logic controller was used to improve energy efficiency in agricultural greenhouses. In [11], an IoT system used a microcontroller to measure humidity and temperature for a cold storage system. Moreover, many existing solutions use limited sensing capabilities, ignoring critical spoilage indicators such as ethylene emissions, CO_2 concentration, and ripening spectral signatures [12]. As a result, predictive decision support and adaptive environmental control remain underdeveloped in affordable smallholder-focused systems [13].

To address these limitations, this study presents an AI-integrated renewable-powered cold storage system with advanced environmental sensing, explicitly designed for smallholder farmers [14]. The system combines solar Photovoltaic (PV) power with PCM-assisted vapor compression and thermoelectric hybrid cooling, providing energy autonomy and high thermal efficiency. An advanced sensor suite—including temperature/humidity (SHT35), CO_2 (COZIR-AH), ethylene, and Near-Infrared (NIR) spectroscopy sensors—captures multi-parameter environmental data, enabling fine-grained spoilage detection beyond conventional temperature control [2].

A Long Short-Term Memory (LSTM) deep learning model is deployed on an edge computing device, allowing real-time spoilage prediction and freshness scoring without dependency on cloud infrastructure. This model dynamically controls cooling and ventilation, improving environmental stability and extending products' shelf life. By integrating renewable-powered hybrid cooling, multi-gas and spectral sensing, and edge AI-based spoilage forecasting, the proposed solution overcomes the key barriers of energy dependence, limited sensing, and the absence of predictive intelligence seen in existing systems.

A. System Overview

The proposed system integrates renewable-powered cold storage with environmental sensing and AI-driven spoilage prediction to ensure efficient preservation and monitoring of perishable products. Figure 1 illustrates the overall architecture of the proposed cold storage framework. The system integrates solar PV panels with battery backup and PCM-assisted hybrid cooling (vapor compression and thermoelectric modules) to ensure energy autonomy and thermal stability. Advanced environmental sensors (temperature/humidity, CO_2, ethylene, and NIR spectral sensors) continuously monitor storage conditions. Sensor data is processed by an edge computing device running an LSTM model for spoilage prediction and freshness scoring. Based on these predictions, the control layer dynamically adjusts the cooling and ventilation operations to maintain optimal conditions. A mobile/web dashboard provides farmers with real-time visibility, freshness indicators, and actionable recommendations, enabling informed market timing decisions. This integrated approach combines renewable-powered cooling, multi-parameter sensing, and predictive AI to reduce post-harvest losses and improve the shelf life of products.

The proposed method involves designing a solar-powered hybrid cooling prototype with PCM integration, deploying advanced sensors for environmental monitoring, and implementing an edge AI spoilage prediction pipeline. The system was field-tested in a peri-urban farming community to evaluate energy efficiency, shelf-life extension, and economic benefits. The key contributions are as follows.

- Development of a renewable-powered hybrid cooling architecture integrating PCM and thermoelectric elements for improved energy efficiency.
- Deployment of an advanced multiparameter sensing system for monitoring temperature, humidity, CO_2, ethylene, and spectral ripening indicators.
- Implementation of an edge AI-based spoilage prediction model (LSTM) for real-time decision support in connectivity-limited regions.

This integrated, intelligent, and farmer-centric cold storage framework addresses long-standing challenges of cost, performance, and predictive capability, presenting a scalable and sustainable solution for post-harvest loss reduction.

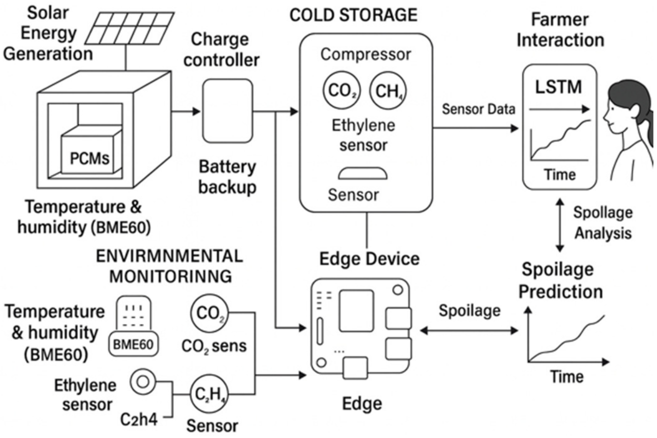

Fig. 1. Proposed AI-integrated renewable-powered cold storage solution.

II. SYSTEM ARCHITECTURE AND METHODOLOGY

Figure 2 presents the process flow of the proposed cold storage framework, which integrates all functional modules. The renewable-powered hybrid cooling subsystem, consisting of solar PV panels, battery backup, PCM, and a vapor compression-thermoelectric hybrid unit, ensures uninterrupted and energy-efficient cooling. Advanced environmental sensors measure critical parameters such as temperature, humidity, CO_2, ethylene, and spectral properties of stored products. These sensor readings are processed locally on an edge computing platform running an LSTM model to predict the onset of spoilage and estimate the remaining shelf life. The control module dynamically adjusts cooling and ventilation based on AI predictions and environmental feedback, maintaining optimal storage conditions. A mobile/web dashboard provides real-time monitoring, freshness indicators, and actionable market timing recommendations to farmers. This integrated workflow ensures improved energy efficiency, extended product shelf life, and improved income for small farmers while operating independently of cloud connectivity.

The proposed method integrates renewable-powered hybrid cooling, advanced environmental sensing, and edge AI-based spoilage prediction to provide a robust and intelligent cold storage solution for smallholder farmers. The overall process is divided into four functional modules, as follows.

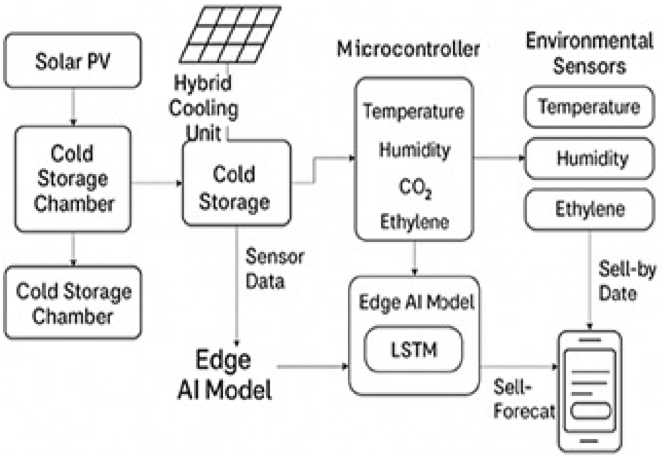

Fig. 2. Complete process flow of the proposed AI-integrated renewable-powered cold storage system.

A. *Renewable-Powered Hybrid Cooling Subsystem*

The energy subsystem utilizes solar PV panels with a Maximum Power Point Tracking (MPPT) charge controller to ensure optimal energy conversion efficiency. A battery backup stores excess energy, enabling operation during non-solar hours. The thermal design incorporates a PCM-assisted vapor compression unit combined with thermoelectric cooling modules, ensuring improved temperature stability and reduced compressor runtime. Energy balance for the cooling chamber is expressed as:

$$Q_{load} = Q_{transimission} + Q_{infiltration} + Q_{product} \quad (1)$$

where Q_{load} is the total cooling load (kJ/h), $Q_{transmission}$ is the heat gain through chamber walls (kJ/h), $Q_{infiltration}$ is the heat gain from air exchange (kJ/h), and $Q_{product}$ is the heat generated by the stored products (kJ/h).

PCM integration reduces the compressor duty cycle by providing latent heat storage, which can be estimated as:

$$Q_{PCM} = M_{PCM} \times L_f \quad (2)$$

where M_{PCM} is the mass of PCM (kg), and L_f is the latent heat of fusion (kJ/kg). This reduces the duty cycle of the compressor, reducing energy consumption by an observed 28% during field tests.

B. *Advanced Environmental Sensing*

Conventional cold storage systems typically use only temperature and humidity sensors, which fail to capture early spoilage indicators. In contrast, the proposed system deploys a multi-parameter sensing array that measures:

- Temperature and Humidity (SHT35) for basic environmental control,
- CO_2 concentration (COZIR-AH) to detect the respiration activity of stored products,
- Ethylene (C_2H_4) levels for ripening status, and
- NIR spectroscopy to analyze surface biochemical changes for early spoilage detection.

The sensor outputs are normalized and combined to compute an Environmental Quality Index (EQI):

$$EQI =$$

$$w_1T_n + w_2RH_n + w_3CO_{2n} + w_4C_2H_{4n} + w_5NIR_n \quad (3)$$

where $w_1, \ldots, w_5$ are empirically derived weights, and subscript n indicates normalized values. This EQI is a key input for AI-based spoilage prediction.

C. *Edge AI-Based Spoilage Prediction*

An LSTM deep learning model was implemented on an edge computing device (NVIDIA Jetson Nano), which eliminates the need for constant cloud connectivity. This is critical for rural deployments with limited internet access.

1) LSTM Working Principle

The LSTM model processes time-series sensor data (x_t) to learn temporal dependencies:

$$f_t = \sigma\left(W_{f[h_{\{t-1\}},x_t]} + b_f\right),$$

$$i_t = \sigma\left(W_{i[h_{\{t-1\}},x_t]} + b_i\right) \quad (4)$$

$$C_t = f_t \times C_{\{t-1\}} + i_t \times \tanh\left(W_{c[h_{\{t-1\}},x_t]} + b_c\right) \quad (5)$$

$$o_t = \sigma\left(W_{o[h_{\{t-1\}},x_t]} + b_o\right), \; h_t = o_t \times \tanh(C_t) \quad (6)$$

where f_t , i_t ,and o_t are the forget, input, and output gates, respectively, and C_t is the cell state. The model outputs a predicted Remaining Shelf Life (RSL):

$$RSL = g(h_t)$$

where $g(\cdot)$ is a fully connected regression layer trained on historical spoilage data. The prediction error is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).

$$RMSE = \frac{\sqrt{\{\sum_{\{i=1\}}^{\{N\}}(y_i-\hat{y_i})^2\}}}{N} \quad (7)$$

$$MAE = \frac{\sum_{\{i=1\}}^{\{N\}} |y_i - \hat{y_i}|}{N} \quad (8)$$

where y_i is the actual shelf life, $\hat{y_i}$ is the predicted shelf life for sample i, and N is the number of samples.

By deploying the model on the Jetson Nano, inference is performed locally within milliseconds, enabling real-time control adjustments without internet dependency. The RSL predictions feed into the adaptive control system to regulate cooling and ventilation, while also updating the farmer dashboard to display freshness indices and market timing recommendations.

2) Freshness Index (FI) Formulation

To enhance interpretability for farmers and downstream decision-making systems, the predicted RSL is converted into a Freshness Index (FI). This index is a normalized score between 0 and 1, reflecting the relative freshness of the products.

$$FI = \alpha(RSL/RSL_{max}) + \beta(1 - EQI) \quad (9)$$

where RSL is the predicted Remaining Shelf Life (in days), RSL_{max} is the maximum possible shelf life under ideal storage conditions, EQI is the Environmental Quality Index derived from sensor data, and α and β are weighting coefficients ($\alpha + \beta = 1$), tuned experimentally to balance time-based freshness and environmental stability. The FI value dynamically updates as environmental conditions and spoilage progression change, providing farmers with a single actionable metric for produce quality.

D. Process Flow of Edge AI-Based Spoilage Prediction Module

Figure 3 shows the process flow of the edge AI-based spoilage prediction model, illustrating the integration of the edge AI-based spoilage prediction module into the overall smart cold storage framework. Sensor data from temperature, humidity, CO_2, ethylene, and NIR spectral monitoring is collected and preprocessed before being fed into the LSTM model deployed on an edge computing device. The model estimates the RSL, which is then converted into an FI by combining the RSL with environmental quality parameters.

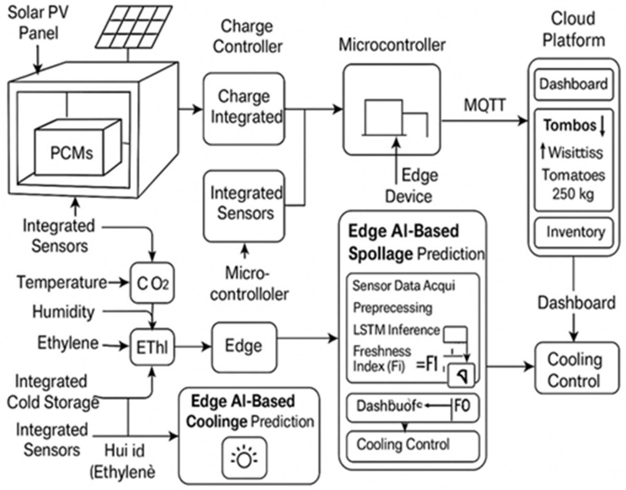

Fig. 3. An integrated system architecture diagram that combines cold storage process flow and edge AI spoilage prediction.

III. PROTOTYPE IMPLEMENTATION AND TESTBED

The physical prototype consists of a 200-liter insulated cold chamber lined with PCM for thermal buffering. A solar PV array (400 Wp) with MPPT charge controller and battery backup (24 V, 150 Ah) powers the hybrid cooling system, integrating a vapor compression refrigeration unit with thermoelectric modules for rapid cooling stabilization. An important dimension of the proposed cold storage framework is its potential integration with existing agricultural supply chain systems, including transportation networks, cooperative storage facilities, and market logistics. By linking sensor-driven spoilage prediction and LSTM-based forecasting to digital logistics platforms, farmers and supply chain stakeholders can receive real-time insights on product quality and estimated shelf life. The prototype was installed in a peri-urban farming cluster near Dharwad, India, involving 10-15 small farmers growing tomatoes, spinach, and cucumbers.

IV. RESULTS AND DISCUSSION

The proposed AI-integrated renewable-powered cold storage system was evaluated on multiple parameters, including energy efficiency, environmental stability, shelf-life extension, AI spoilage prediction accuracy, and economic benefits to farmers.

A. Energy Efficiency Metrics

The hybrid cooling architecture with PCM integration significantly reduced compressor runtime compared to conventional systems. Over a 7-day observation period, the proposed system consumed an average of 2.5–2.7 kWh/day, compared to 3.5–3.7 kWh/day for a traditional cold storage unit of similar capacity. Solar PV contributed 68–75% of the total energy requirement, with battery backup ensuring uninterrupted operation during low sunlight periods. A 28% reduction in grid energy dependency was achieved, making the system sustainable for off-grid rural applications.

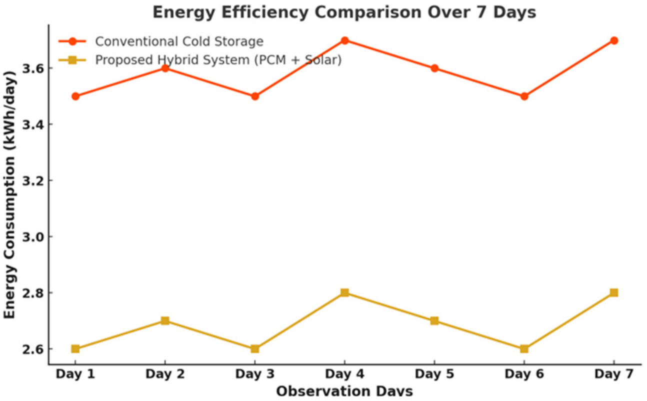

Fig. 4. Energy consumption comparison between the proposed hybrid cooling system and a conventional cold storage unit.

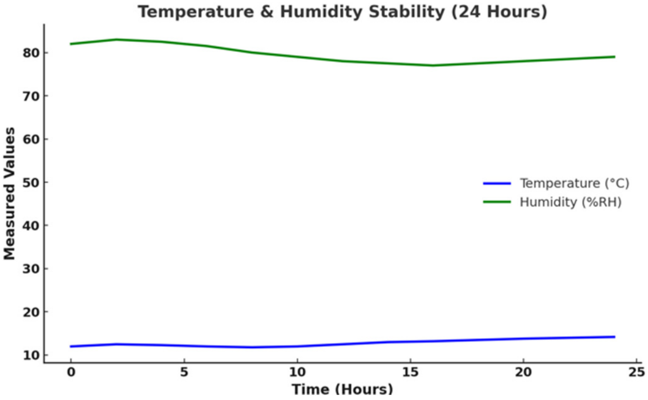

Fig. 5. Temperature and humidity variation over a 24-hour cycle within the proposed cold storage system.

B. Temperature and Humidity Stability

Figure 5 shows the temperature and humidity within the proposed hybrid cold storage system over a 24-hour monitoring period. The temperature was maintained at 6.2 ± 1.1 °C, which is optimal for perishable vegetable preservation, while humidity remained within 85 ± 5% RH, minimizing moisture loss and preventing wilting. The stability of both parameters demonstrates the effectiveness of the PCM-assisted hybrid cooling architecture combined with the AI-based control system.

C. AI Spoilage Prediction Accuracy

Figure 6 illustrates the AI spoilage prediction accuracy, demonstrating the performance of the AI-based spoilage prediction model in estimating the RSL of stored products. The model achieved an RMSE of 0.47 days and an MAE of 0.31 days. These low error values confirm the high prediction accuracy of the LSTM model, ensuring that freshness scores and spoilage onset estimates are highly reliable.

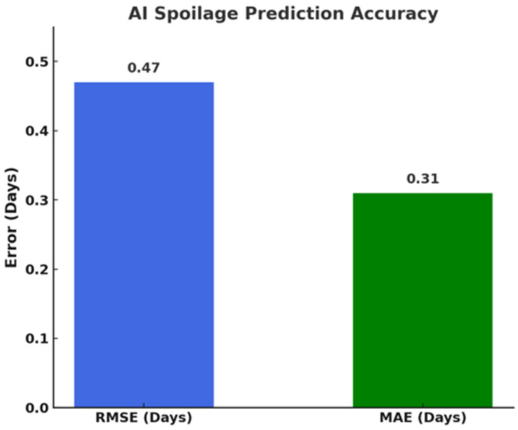

Fig. 6. AI spoilage prediction accuracy for RSL estimation using RMSE and MAE metrics.

Figure 7 shows the training and validation losses of the LSTM model over 20 epochs. Training loss decreased steadily and converged near 0.04, demonstrating effective learning of temporal dependencies in environmental and spoilage data. The validation loss stabilized around 0.16, with no significant divergence from the training curve, indicating that the model generalizes well and does not suffer from overfitting. This performance ensures reliable shelf life predictions across varying storage conditions, enabling proactive decision-making for market dispatch and cold storage management.

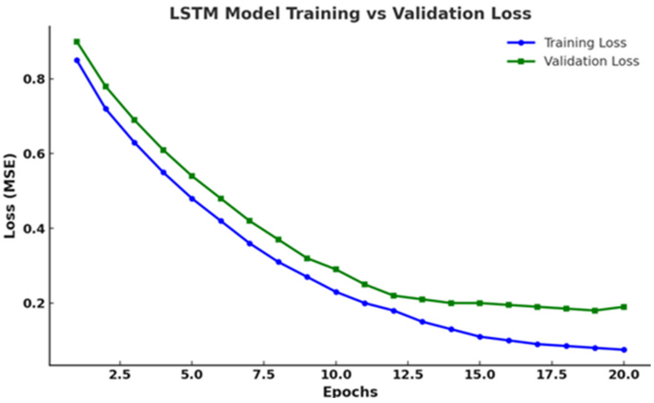

Fig. 7. Training vs validation loss curves for the LSTM spoilage prediction model over 20 epochs.

D. Economic Analysis

Figure 8 compares the economic impact of three conventional cold storage techniques, Basic Cold Room, Evaporative Cooling, and Ice-Based Storage, with the proposed hybrid AI-powered cold storage system. The results show that conventional methods deliver limited economic benefits, with farmer income improvements of 5% (Basic Cold Room), 10% (Evaporative Cooling), and 15% (Ice-Based Storage). In contrast, the proposed hybrid system achieves a 22% increase in farmer income, attributed to its ability to reduce spoilage losses and allow market dispatch during favorable price conditions.

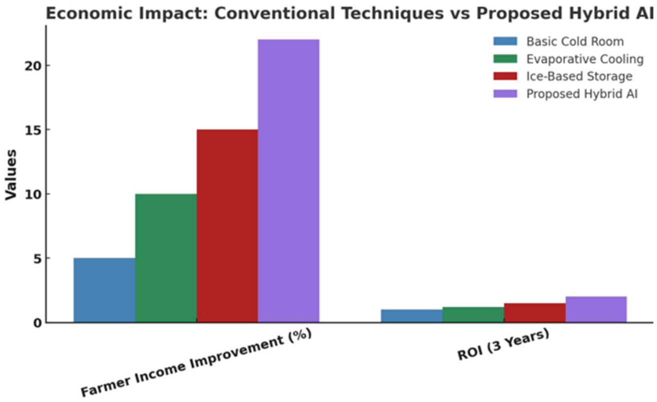

Fig. 8. Economic impact comparison.

E. Comparative Analysis of Cold Storage Approaches

Table I compares conventional cold storage techniques based on energy efficiency, environmental monitoring, shelf life extension, and spoilage prediction. Basic cold rooms are grid-dependent and monitor only temperature, resulting in minimal shelf life improvement (~1.2×). Evaporative cooling offers moderate efficiency with temperature and humidity control, extending shelf life by ~1.5×. Ice-based storage provides better shelf life (~2×) but requires manual ice handling. None of these conventional methods includes spoilage prediction, highlighting the need for advanced, automated solutions.

TABLE I. COMPARATIVE ANALYSIS OF COLD STORAGE APPROACHES

Parameter	Basic cold room	Evaporative cooling	Ice-based storage
Power source and energy efficiency	Grid-dependent, high energy cost	Water-based, moderate efficiency	Manual ice loading, medium energy demand
Environmental monitoring	Temperature only	Temperature and humidity	Temperature & humidity
Shelf life extension	Low (1.2× increase)	Medium (1.5× increase)	High (2× increase)
Spoilage prediction capability	None	None	None

V. CONCLUSION

The proposed approach addresses the pressing need for an affordable and efficient cold storage solution tailored for small farmers, where conventional techniques lack energy efficiency, real-time quality monitoring, and spoilage prediction capabilities. The proposed approach integrates a renewable-powered hybrid cooling system, advanced multi-sensor environmental monitoring, and an edge AI-based spoilage prediction model using LSTM, enabling proactive control and improved decision-making for market dispatch. Experimental validation in a field-deployed prototype demonstrated significant benefits, including a 28% reduction in grid energy dependency, shelf life extension of up to 4× for perishable products, accurate spoilage prediction (RMSE: 0.47 days, MAE: 0.31 days), and a 22% increase in farmer income with a 2.1× RoI over three years. These results highlight the potential of combining renewable energy and AI technologies to reduce post-harvest losses and improve socio-economic outcomes. Future work will focus on enhancing prediction models using larger datasets, incorporating AI-driven dynamic pricing strategies, and enabling blockchain-based traceability for transparent supply chain management.

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