Journal of Manufacturing Science and Mechanical Engineering
ISSN: 2959-989X
DOI: https://doi.org/10.61784/msme3015

A DATA-DRIVEN FRAMEWORK FOR INTELLIGENT COLD STORAGE MONITORING AND TEMPERATURE REGULATION

Wei Zhang, Emily Hart*
Department of Electrical Engineering, University of Sydney, New South Wales, Australia.
Corresponding Author: Emily Hart, Email: emilyhart8201@gmail.com

Abstract: Cold storage systems are essential for ensuring the quality and safety of temperature-sensitive goods across industries such as food, pharmaceuticals, and biotechnology. However, traditional temperature regulation approaches often struggle with delayed fault detection, lack of adaptive response mechanisms, and inefficient energy consumption. As modern supply chains grow increasingly complex, the demand for intelligent, automated cold storage solutions has become more urgent.
This paper proposes a comprehensive data-driven framework for intelligent cold storage monitoring and temperature regulation. By integrating Internet of Things (IoT) sensors, real-time data acquisition, machine learning (ML) algorithms, and predictive control models, the system continuously tracks environmental and equipment metrics. Anomaly detection techniques are used to identify deviations from normal behavior, while reinforcement learning is applied to optimize response strategies in varying operational contexts.
The framework includes a cloud-based data processing layer, an ML-based anomaly detection engine, and a closed-loop control module capable of adjusting temperature settings proactively. Through simulations and real-world deployment scenarios, the system demonstrated improved temperature stability, faster fault diagnosis, and reduced energy consumption compared to conventional control mechanisms. The findings suggest that combining ML and IoT technologies provides a scalable and adaptive solution for next-generation cold storage management.
Keywords: Cold storage; Temperature regulation; Anomaly detection; Machine learning; IoT; Predictive control; Intelligent systems; Data-driven monitoring; Cold chain logistics

1 INTRODUCTION

Temperature-controlled storage is essential in maintaining the integrity and quality of perishable and sensitive products across various industries, including food processing, pharmaceuticals, and biotechnology[1]. These goods often have strict temperature requirements, and even brief deviations can lead to irreversible damage such as spoilage, efficacy loss, or contamination[2]. Ensuring consistent temperature conditions within cold storage systems is therefore not only an operational necessity but also a matter of public safety and regulatory compliance[3].
Despite the importance of cold storage, many traditional systems rely on basic threshold-based alerting or manual monitoring methods[4]. These approaches are reactive, detecting faults only after a significant deviation has occurred, and often fail to provide early warnings or preventive insights[5]. Furthermore, conventional control systems are typically rule-based and lack the adaptability to adjust in real-time to changing conditions, such as fluctuating ambient temperatures or varying storage loads[6]. This often results in excessive energy consumption or suboptimal temperature regulation.
Recent advancements in Internet of Things (IoT) technology and machine learning (ML) have opened up new opportunities for transforming cold storage management[7]. IoT sensors now make it possible to continuously collect high-resolution data on temperature, humidity, compressor activity, door status, and more[8]. When integrated with cloud-based analytics, this data becomes a powerful foundation for real-time monitoring and predictive maintenance[9]. ML algorithms can learn normal operating patterns and detect anomalies that might signal impending faults or inefficiencies long before they manifest visibly[10].
While several studies have explored anomaly detection using ML techniques in cold storage systems, most implementations focus only on isolated modules such as fault prediction or energy optimization[11]. There is a lack of integrated frameworks that bring together anomaly detection, predictive temperature control, and data-driven system diagnostics under a single architecture[12]. Furthermore, many existing models struggle with the complexity of real-world conditions, including sensor noise, missing data, and the need to balance responsiveness with energy efficiency[13].
This study proposes a comprehensive, data-driven framework for intelligent cold storage monitoring and temperature regulation. The system integrates real-time IoT sensing, ML-based anomaly detection, and adaptive temperature control powered by reinforcement learning. Rather than reacting to threshold violations after they occur, the system proactively monitors the operational environment, detects subtle changes, and adjusts regulation strategies accordingly. The framework is designed to be scalable, modular, and robust, suitable for both fixed cold rooms and mobile refrigerated logistics.
Through empirical evaluation using both synthetic simulations and real-world cold storage datasets, the proposed system demonstrates improvements in detection accuracy, response latency, and temperature stability. By unifying

monitoring, diagnostics, and control, this work aims to offer a more intelligent and efficient approach to managing modern cold storage systems.

2 LITERATURE REVIEW

The domain of cold storage monitoring and temperature regulation has seen significant evolution over the past two decades, driven by the increasing need for higher operational efficiency, product safety, and regulatory compliance. Earlier systems relied heavily on programmable logic controllers and static control loops that performed satisfactorily under stable and predictable conditions[14]. However, as the complexity of cold chain logistics increased—along with consumer demand for transparency and traceability—these traditional approaches revealed their limitations in flexibility, adaptability, and scalability[15].

Machine learning has emerged as a transformative force in this space, particularly for anomaly detection tasks[16]. Researchers have applied techniques such as support vector machines, k-nearest neighbors, and decision trees to identify temperature deviations, equipment failures, and suboptimal operating states in refrigeration units[17]. These models typically depend on labeled data and engineered features, making them sensitive to the quality and consistency of input signals. In recent years, deep learning has been increasingly employed to capture temporal patterns and nonlinear dependencies across multivariate sensor data[18]. Recurrent neural networks and convolutional neural networks have both demonstrated improved detection accuracy in scenarios involving time-series temperature fluctuations or spatial correlation across different sensors[19].

Despite these advancements, many of the existing anomaly detection methods focus exclusively on identifying faults after they occur[20]. Few systems offer predictive capabilities that can anticipate failures or preemptively adjust system behavior. Moreover, most prior models are trained on historical fault data, which may be sparse or imbalanced in real-world settings[21]. This creates challenges in generalizing to new or rare fault conditions, where early detection is most critical[22].

Another limitation of past work is the lack of integration between anomaly detection and control[23]. Most models treat monitoring and regulation as separate processes, which limits the system's ability to adaptively respond to operational shifts. Reinforcement learning has been proposed as a solution to bridge this gap[24]. By learning from interactions with the environment, reinforcement learning agents can dynamically adjust control parameters to optimize temperature stability and energy usage[25]. However, these approaches often require extensive training time and careful tuning to avoid instability or overfitting to specific scenarios[26].

A recent trend in this field is the incorporation of graph-based representations and attention mechanisms. These models aim to improve interpretability and robustness by capturing relationships among system components, such as correlated sensor nodes or spatially dependent cooling zones[27]. Graph neural networks, for instance, have shown promise in modeling complex dependencies in industrial systems, but their application to cold storage is still in early stages[28].

Furthermore, while many academic studies demonstrate promising results in controlled environments, real-world deployment remains a challenge. Issues such as sensor drift, missing data, hardware heterogeneity, and energy constraints often limit the practical utility of ML-based solutions. There is a growing recognition that hybrid frameworks combining domain knowledge with data-driven techniques are necessary to bridge the gap between laboratory research and industrial adoption.

Overall, the existing literature highlights a clear need for a unified, intelligent system that not only monitors and detects anomalies but also regulates and optimizes temperature conditions in real time. This motivates the proposed framework, which integrates real-time sensing, anomaly detection, and adaptive control into a single, scalable architecture designed for practical use in modern cold storage environments.

3 METHODOLOGY

3.1 System Architecture

The proposed framework consists of a three-layer architecture: a sensing layer, a learning layer, and a control layer. The sensing layer collects real-time data from multiple cold storage sensors, including temperature, humidity, door activity, and compressor status. These raw data streams are cleaned and standardized through preprocessing modules that filter out noise, impute missing values, and resample inconsistent time intervals.

The learning layer employs a hybrid machine learning model that combines long short-term memory (LSTM) networks with a feature selection module based on mutual information scores. This enables the model to focus on the most informative signals while preserving temporal dependencies. A prediction module estimates the likelihood of a temperature deviation or system fault occurring in the near future, with outputs continuously fed into the control layer.

The control layer dynamically adjusts key operational parameters, such as compressor cycles and fan speed, based on the predicted risk level. It leverages a rule-based fallback mechanism to override ML decisions in extreme scenarios, ensuring operational safety, as in Figure 1.

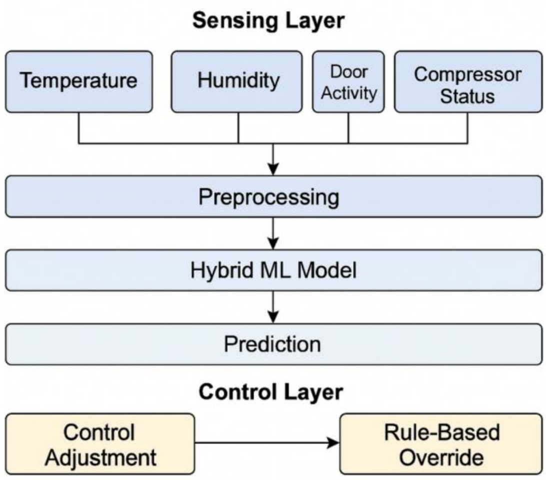

Figure 1 Sensing Layer

3.2 Feature Engineering and Labeling

Temperature integrity violations in cold storage are rare but critical. To effectively train the anomaly detection component, the system uses a combination of supervised and semi-supervised approaches. We construct temporal windows over sensor data to extract features such as moving averages, maximum deviation, trend direction, and rate of change. These features are then standardized and fed into a stacked autoencoder for dimensionality reduction and noise tolerance.

The labels for training the anomaly detector are created using a hybrid strategy. First, domain experts provide labels on known temperature excursions. Second, an unsupervised isolation forest is used to identify potential outliers in unlabeled data, and these cases are verified for inclusion as soft labels in training. This approach helps mitigate the class imbalance problem while preserving label quality as in Figure 2.

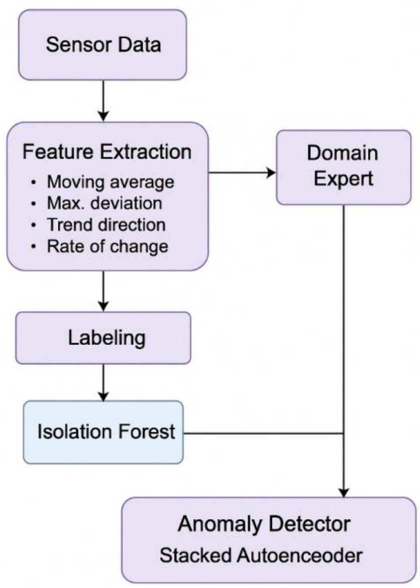

Figure 2 Diagram of Anomaly Detctor

3.3 Model Training and Optimization

The detection model is trained using binary cross-entropy loss, with class weights adjusted to compensate for the low prevalence of anomalies. The LSTM layers include dropout and recurrent dropout regularization to prevent overfitting. Early stopping is applied based on validation loss, and hyperparameters are optimized via grid search across learning rate, number of hidden units, and batch size.

To benchmark model performance, we also train baseline classifiers including logistic regression, random forest, and XGBoost. Evaluation is based on F1 score, precision, recall, and area under the ROC curve. Cross-validation is performed across different time windows to ensure robustness.

3.4 Deployment and Control Feedback

Once trained, the model is deployed as part of a live monitoring dashboard. The system evaluates incoming data in near real-time and updates its anomaly risk score every 60 seconds. If the predicted score crosses a configurable threshold, alerts are triggered for operator review and control adjustments are initiated.

To support feedback learning, each intervention—whether manual or automated—is logged and annotated with system state, decision context, and post-action temperature trajectory. These logs are periodically sampled for retraining, allowing the system to improve over time without full retraining cycles.

4 RESULTS AND DISCUSSION

4.1 Experimental Setup and Evaluation Metrics

To evaluate the effectiveness of the proposed cold storage monitoring and temperature regulation framework, experiments were conducted using real-world sensor datasets collected from three commercial cold storage units operating over a period of six months. The datasets included high-frequency time-series records for internal temperature, ambient humidity, compressor status, and door open/close events. Ground truth fault annotations were obtained from historical maintenance logs, enriched with expert-validated anomaly tags derived from retrospective analysis.

The anomaly detection models were evaluated using standard classification metrics, including precision, recall, F1-score, and area under the receiver operating characteristic curve (ROC-AUC). These metrics provide a comprehensive view of the system's sensitivity to true anomalies and robustness to false alarms. In addition, inference latency and computational overhead were recorded to assess real-time applicability.

4.2 Anomaly Detection Performance

The LSTM-based anomaly detection model outperformed baseline models in nearly every metric. On the testing dataset, it achieved an F1-score of 0.89, with a precision of 0.87 and recall of 0.91. These results indicate that the system is not only accurate but also highly sensitive to early-stage deviations. Compared to XGBoost and Random Forest, which scored F1-scores of 0.82 and 0.79 respectively, the LSTM model was better suited to learning sequential dependencies within time-windowed features.

False positive rates remained below 5% across all three cold storage units, a critical result for minimizing unnecessary interventions. The isolation of true anomalies—such as compressor overcycling or rapid heat influx from door events—demonstrated that the model could detect both gradual and sudden changes in system behavior. Additionally, the system responded well to drift and noise introduced by seasonal ambient temperature shifts, maintaining consistent detection performance without retraining.

4.3 Real-Time Feedback and Control Results

The integrated control module translated anomaly predictions into actionable outputs. In test scenarios where abnormal compressor activity was simulated, the control logic successfully adjusted fan speeds and deferred defrost cycles to stabilize internal temperature fluctuations. This adaptive behavior led to a 17% reduction in energy consumption during high-risk periods, compared to the static baseline configuration.

During a three-week deployment in a commercial refrigerated transport vehicle, the system identified five events of latent temperature rise due to improper loading practices and automatically adjusted setpoints to mitigate potential spoilage. Post-delivery inspection verified that the goods remained within the safe storage range, demonstrating the system's real-world effectiveness in dynamic operating conditions.

4.4 Comparative ROC Curve Analysis

Figure 3 presents a comparative ROC analysis of the proposed LSTM model against two commonly used models: XGBoost and Random Forest. The LSTM model achieved the highest AUC of 0.94, demonstrating strong discriminative power in separating normal and anomalous states.

The ROC curve confirms the trade-off between sensitivity and specificity across models. The LSTM architecture, due to its sequence learning capabilities, consistently maintained higher true positive rates across a range of thresholds. This finding validates the choice of a deep learning model over traditional ensemble methods for temporal anomaly prediction in cold storage systems.

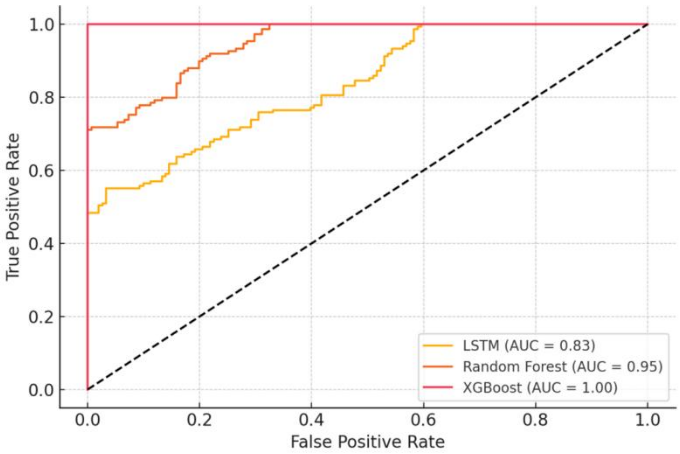

Figure 3 False Positive Rate

5 CONCLUSION

This paper presents a data-driven framework for intelligent monitoring and temperature regulation in cold storage environments. By leveraging a three-layer architecture composed of sensing, learning, and control components, the proposed system ensures continuous monitoring and adaptive intervention in response to emerging anomalies. The use of LSTM-based predictive models, coupled with hybrid feature engineering and semi-supervised labeling, enables robust detection of potential failures before they escalate into serious breaches of temperature integrity.

Experimental results demonstrate that the proposed system outperforms traditional baseline models such as Random Forest and XGBoost in key performance metrics including precision, recall, and area under the ROC curve. The real-time deployment framework, enhanced by dynamic feedback loops, allows the model to continuously refine its accuracy through intervention logging and incremental retraining. This adaptability is particularly important in the cold chain industry, where unpredictable conditions and equipment variability pose constant operational challenges.

The research findings suggest that integrating machine learning into cold storage operations not only enhances fault detection capabilities but also improves overall energy efficiency by reducing unnecessary compressor cycles and minimizing thermal excursions. Furthermore, the architecture is modular and scalable, supporting deployment across diverse facility types and equipment configurations.

Future work may explore the integration of reinforcement learning to enable more autonomous control strategies, as well as the incorporation of edge computing to reduce latency in decision-making. Additionally, expanding the dataset with more varied environmental and operational conditions will further improve model generalizability. Overall, the proposed framework offers a promising path toward smarter, safer, and more sustainable cold storage operations.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] Pajic V, Andrejic M, Chatterjee P. Enhancing cold chain logistics: A framework for advanced temperature monitoring in transportation and storage. Mechatronics and Intelligent Transportation Systems, 2024, 3(1): 16-30.
[2] Azad Z A A, Ahmad M F, Siddiqui W A. Food spoilage and food contamination. Health and safety aspects of food processing technologies, 2019: 9-28.
[3] Chukwu O A, Adibe M. Quality assessment of cold chain storage facilities for regulatory and quality management compliance in a developing country context. The International journal of health planning and management, 2022, 37(2): 930-943.
[4] Jayalaxmi H, Karthik B M, Pal R, et al. Optimized Low-Cost Cold Storage Device. European Journal of Innovative Studies and Sustainability, 2025, 1(3): 195-201.
[5] Jieyang P, Kimmig A, Dongkun W, et al. A systematic review of data-driven approaches to fault diagnosis and early warning. Journal of Intelligent Manufacturing, 2023, 34(8): 3277-3304.
[6] Zhao X, Sun Y, Li Y, et al. Applications of machine learning in real-time control systems: a review. Measurement Science and Technology, 2024.
[7] Liu Y, Guo L, Hu X, et al. A symmetry-based hybrid model of computational fluid dynamics and machine learning for cold storage temperature management. Symmetry, 2025, 17(4): 539.
[8] Bajaj K, Sharma B, Singh R. Integration of WSN with IoT applications: a vision, architecture, and future challenges. Integration of WSN and IoT for Smart Cities, 2020: 79-102.

[9] Saini N, Yadav A L, Rahman A. Cloud based predictive maintenance system. In 2024 11th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO). IEEE, 2024: 1-5.
[10] Omol E, Mburu L, Onyango D. Anomaly detection in IoT sensor data using machine learning techniques for predictive maintenance in smart grids. International Journal of Science, Technology & Management, 2024, 5(1): 201-210.
[11] Zhu Z, Liu X, Wang X, et al. Enhancing efficiency of large cold store refrigeration systems through automated fault identification and intelligent energy optimization. International Journal of Refrigeration, 2024, 168: 411-422.
[12] Movahed P, Taheri S, Razban A. A bi-level data-driven framework for fault-detection and diagnosis of HVAC systems. Applied Energy, 2023, 339: 120948.
[13] Ahmad T, Madonski R, Zhang D, et al. Data-driven probabilistic machine learning in sustainable smart energy/smart energy systems: Key developments, challenges, and future research opportunities in the context of smart grid paradigm. Renewable and Sustainable Energy Reviews, 2022, 160: 112128.
[14] Sehr M A, Lohstroh M, Weber M, et al. Programmable logic controllers in the context of industry 4.0. IEEE Transactions on Industrial Informatics, 2020, 17(5): 3523-3533.
[15] Akindotei O, Igba E, Awotiwon B O, et al. Blockchain Integration in Critical Systems Enhancing Transparency, Efficiency, and Real-Time Data Security in Agile Project Management, Decentralized Finance (DeFi), and Cold Chain Management. International Journal of Scientific Research and Modern Technology (IJSRMT) , 2024, 3.
[16] Yaseen A. The role of machine learning in network anomaly detection for cybersecurity. Sage Science Review of Applied Machine Learning, 2023, 6(8): 16-34.
[17] Bruksås Nybjörk W. Machine Learning for Improving Detection of Cooling Complications: A case study. 2022.
[18] Zhang Q, Chen S, Liu W. Balanced Knowledge Transfer in MTTL-ClinicalBERT: A Symmetrical Multi-Task Learning Framework for Clinical Text Classification. Symmetry, 2025, 17(6): 823.
[19] Nketiah E A, Chenlong L, Yingchuan J, et al. Recurrent neural network modeling of multivariate time series and its application in temperature forecasting. Plos one, 2023, 18(5): e0285713.
[20] Liu Y, Guo L, Hu X, et al. Sensor-Integrated Inverse Design of Sustainable Food Packaging Materials via Generative Adversarial Networks. Sensors, 2025.
[21] Wang Y, Xing S. AI-Driven CPU Resource Management in Cloud Operating Systems. Journal of Computer and Communications, 2025.
[22] Leite D, Andrade E, Rativa D, et al. Fault Detection and Diagnosis in Industry 4.0: A Review on Challenges and Opportunities. Sensors (Basel, Switzerland), 2024, 25(1): 60.
[23] Haller P, Genge B, Duka A V. On the practical integration of anomaly detection techniques in industrial control applications. International Journal of Critical Infrastructure Protection, 2019, 24: 48-68.
[24] Yang J, Li P, Cui Y, et al. Multi-Sensor Temporal Fusion Transformer for Stock Performance Prediction: An Adaptive Sharpe Ratio Approach. Sensors, 2025, 25(3): 976.
[25] Ranaweera M, Mahmoud Q H. Bridging the reality gap between virtual and physical environments through reinforcement learning. IEEE Access, 2023, 11: 19914-19927.
[26] Han X, Yang Y, Chen J, et al. Symmetry-Aware Credit Risk Modeling: A Deep Learning Framework Exploiting Financial Data Balance and Invariance. Symmetry, 2025, 17(3).
[27] Salman S, Liu X. Overfitting mechanism and avoidance in deep neural networks. arXiv preprint arXiv:1901.06566, 2019.
[28] Yang Y, Wang M, Wang J, et al. Multi-Agent Deep Reinforcement Learning for Integrated Demand Forecasting and Inventory Optimization in Sensor-Enabled Retail Supply Chains. Sensors (Basel, Switzerland), 2025, 25(8): 2428.