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Prediction of Daily Ice Crystal Demand Using Modified Bi-xLSTM

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Abstract

This study aims to develop an improved daily demand prediction model for crystal ice by integrating weather data, Google search trends, and sales history using a modified Bi-xLSTM architecture. Forecasting perishable goods is critical for Micro, Small, and Medium Enterprises (MSMEs) to prevent stockouts. However, traditional models often fail to capture dynamic non-linear demand factors. We propose a Bidirectional Extended Long Short-Term Memory (Bi-xLSTM) model incorporating temperature, humidity, rainfall, and "crystal ice" search trends. The model was trained 365 of historical sales data from a local MSME. Implementation involved data normalization, sliding window sequencing, and hyperparameter tuning. Evaluation using a confusion matrix reveals that the model achieved an Accuracy of 90%, with a notable Recall of 99.98% and Precision of 81.25%. This high-recall strategy minimizes the risk of stockouts (Type II errors), effectively acting as a safety buffer for inventory management. These results demonstrate that the modified Bi-xLSTM is a viable, risk-averse decision-support tool for MSMEs in the F&B sector.

Key Words*: *Artificial Intelligence, Bi-xLSTM, Crystal Ice, Demand Forecasting, MSME.

Abstrak

Penelitian ini bertujuan untuk mengembangkan model prediksi permintaan harian es kristal yang lebih baik dengan mengintegrasikan data cuaca, tren pencarian Google, dan riwayat penjualan menggunakan arsitektur Bi-xLSTM yang dimodifikasi. Peramalan barang yang mudah rusak sangat penting bagi Usaha Mikro, Kecil, dan Menengah (UMKM) untuk mencegah kehabisan stok. Namun, model tradisional sering gagal menangkap faktor permintaan non-linear yang dinamis. Kami mengusulkan model Bidirectional Extended Long Short-Term Memory (Bi-xLSTM) yang menggabungkan suhu, kelembapan, curah hujan, dan tren pencarian "es kristal". Model dilatih menggunakan 365 hari data penjualan historis dari UMKM lokal. Implementasi melibatkan normalisasi data, pengurutan sliding window, dan tuning hyperparameter. Evaluasi menunjukkan bahwa model mencapai Akurasi 90%, dengan Recall 99,98% dan Presisi 81,25%. Strategi recall tinggi ini meminimalkan risiko kehabisan stok (kesalahan Tipe II), yang secara efektif bertindak sebagai penyangga keamanan untuk manajemen inventaris. Hasil ini menunjukkan bahwa Bi-xLSTM yang dimodifikasi adalah alat pendukung keputusan yang layak bagi UMKM di sektor F&B.

Kata Kunci: **Bi-xLSTM, Es Kristal, Kecerdasan, Buatan, Peramalan Permintaan, UMKM**

Introduction

In the highly competitive food and beverage (F&B)[1], [2] industry, the ability of Micro, Small, and Medium-sized Enterprises (MSMEs)[3] to accurately forecast sales is a cornerstone of operational efficiency. This challenge is increasingly complex for perishable products like crystal ice, where prediction errors lead directly to financial losses from overstocking or lost revenue from stockouts. Unlike large corporations, MSMEs often rely on managerial intuition or traditional statistical models like ARIMA[4] ,. While effective for linear patterns, these methods fail to capture complex demand dynamics influenced by external factors such as weather conditions and social trends.

Deep Learning (DL)[5], [6], [7] architectures, such as Long Short-Term Memory (LSTM)[8], [9], [10], [11], [12], [13], [16], [17], [18] and Gated Recurrent Units (GRU), have proven superior for sequential data forecasting[14], [15], [19] ,. However, their adoption in MSMEs is hindered by high implementation costs, technical complexity, and the requirement for massive historical datasets that small businesses rarely possess. Crucially, specific research targeting forecasting problems for products with extremely short shelf lives, such as crystal ice, is still relatively limited in the literature. Previous studies have largely focused on energy or large-scale agriculture, leaving a significant gap in accessible, high-precision inventory tools tailored to the resource constraints of MSMEs.

To bridge this gap, this research proposes a daily demand prediction model using a modified Bidirectional Extended Long Short-Term Memory (Bi-xLSTM) architecture. This approach balances technological sophistication with practical implementation for small enterprises.

The specific contributions of this study are:

1. Application of Modified Bi-xLSTM: We implement the latest generation xLSTM architecture with a bidirectional topology, specifically optimized to handle volatile time-series data with limited historical depth ,.
2. Multi-Modal Feature Integration: The model uniquely integrates physiological demand drivers (BMKG weather data) with behavioral indicators (Google Trends search volume) to enhance predictive context beyond simple sales history.
3. Risk-Averse Decision Support: We demonstrate a model strategy that prioritizes high recall to minimize stockouts, aligning intrinsically with the asymmetric risk profile of MSMEs where service continuity is critical.

Research Methodology Metodology

This research adheres to the Cross-Industry Standard Process for Data Mining (CRISP-DM) framework [20], adapted into a streamlined four-stage workflow: Data Extraction, Data Processing, Data Training, and Model Implementation. This structured approach ensures the predictive model aligns with the practical business requirements of the MSME that show on Figure 1.

Figure 1 Flow implementation for research methodology

A. Data Source

To ensure high predictive accuracy and capture the complex, non-linear demand patterns inherent in the crystal ice market, this study utilizes a large-scale dataset derived from heterogeneous sources. The data was aggregated from multiple MSME partners located across various regions in Indonesia.The final dataset consists of a total of 589,266 daily records. This extensive volume of data was specifically selected to provide the deep learning architecture with the complexity and diversity required for robust training, ensuring the model can generalize effectively across different market conditions and geographical nuances. The dataset is categorized into two distinct types:

1. **Primary Data (Internal):** This data serves as the ground truth and is derived from the aggregated daily sales logs of the partner MSMEs. Originally recorded as continuous variables (sales volume in kg), the data was transformed into a binary classification format to align with decision-support needs. The target variable, 'Ice Need' (y),, is encoded as follows:
   - $y = 1$: **High Demand** (Inventory replenishment or extra production required).
   - $y = 0$: **Low/Normal Demand** (Existing stock is sufficient).
2. **Secondary Data (External):** To capture external drivers of demand, we integrated public data paired spatially with the sales locations:

- Weather Data: Historical daily records from the Meteorology, Climatology, and Geophysics Agency (BMKG), specifically Average Temperature T_{avg}, Relative Humidity (RH), and Rainfall (RR).
- Google Trends: The Search Volume Index (SVI) for the keyword "crystal ice" (es kristal), extracted for each specific region to gauge local consumer interest.

To establish data validity, the descriptive statistics of the numerical features used in this study are presented in Table 1.

Tabel 1 Example BMKG Data Source

Time	Village	Temp (°C)	RH	RR
2025-10-04 14:00	Gubeng	34	70	1
2025-10-04 17:00	Gubeng	31	70	1
2025-10-04 20:00	Gubeng	29	60	2
2025-10-04 23:00	Gubeng	26	60	2

B. Baseline Models for Comparison

To validate the claimed superiority of the proposed modified Bi-xLSTM architecture, this study benchmarks its performance against four established forecasting models widely used in the literature:

1. **ARIMA (AutoRegressive Integrated Moving Average):** A standard statistical baseline for time-series forecasting[4].
2. **LSTM (Long Short-Term Memory):** A standard recurrent neural network used as a deep learning baseline[16], [17], [18].
3. **GRU (Gated Recurrent Unit):** A streamlined variant of LSTM often used for its computational efficiency [14].
4. **Bi-LSTM (Bidirectional LSTM):** A standard bidirectional architecture without the "Extended" (xLSTM) modifications proposed in this study[15].

Comparing the proposed model against these baselines ensures that the improvements in Accuracy and Recall are attributed to the specific architectural innovations (xLSTM modifications) rather than general deep learning capabilities.

C. Data Pre-processing

The data pre-processing stage constitutes a foundational component of the research framework, designed to transform raw, noisy environmental and sales data into a structured format suitable for high-performance deep learning algorithms. This phase involves several crucial systematic steps to ensure data integrity and model convergence. First, the handling of missing values is addressed with rigor. Real-world sensor data from public agencies often suffers from transmission gaps or sensor failures. To maintain the temporal continuity essential for time-series analysis without discarding valuable data points, the mean imputation method is employed. This technique replaces missing entries with the statistical average of the dataset, preserving the overall distribution and preventing the bias that might arise from dropping entire rows of data. Second, to address the issue of differing magnitudes among variables, all numerical features are normalized using the MinMaxScaler algorithm. The raw data features operate on vastly different scales; for instance, temperature typically ranges between 24°C and 34°C, while humidity approaches 100%, and search trends vary from 0 to 100. Such disparities can cause the gradient descent optimization in neural networks to oscillate or fail to converge. The MinMaxScaler transforms all values into a bounded range of [0,1]using the Equation no 1.

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X_{norm} represents the normalized value, X is the original observed value from the dataset, X_{min} is the minimum value recorded for that specific feature column, and X_{max} is the maximum value recorded for that feature column[3]. This transformation stabilizes the training process and ensures that no single feature dominates the model's weight updates solely due to its scale. Thereby stabilizing the training process and ensuring that no single feature dominates the model's weight updates solely due to its scale. Third, the sequential time-series data is converted into a supervised learning format suitable for the Bi-xLSTM architecture. This is achieved using a sliding window technique. The continuous stream of daily data is restructured into input-output pairs, where a specific window of historical data is used to forecast the subsequent step. This study utilizes a look-back period of three days $(t-3, t-2, t-1)$. This specific window size was selected to capture short-term weather fluctuations and immediate consumer trends without introducing excessive noise from distant historical data, thus enabling the model to predict the inventory needs of the following day (t) with high relevance. to reduce computational complexity and mitigate the risk of overfitting a common challenge when applying deep learning to smaller datasets with feature selection was carried out. Rather than using all available meteorological parameters, the model focuses exclusively on the most impactful drivers of ice consumption: average temperature (Tavg), average humidity (RH_avg), and rainfall (RR), which represent the physiological drivers of demand, alongside the Google Trends index, which serves as a behavioral proxy for consumer intent. This parsimonious feature set balances model simplicity with predictive power. The pre-processing data example was shown on Table 2.

Tabel 2 Pre-processing data with data training

Tavg	RHavg	RR	Ice-Need
27.1	82	9	1
25.7	95	24	0
24.5	98	63	0
25.8	90	0	0

D. Model Implementation

The core computational engine of this study is a sophisticated, custom-designed deep learning framework known as the Bidirectional Extended Long Short-Term Memory (Bi-xLSTM). This architecture represents a significant evolutionary leap from canonical LSTM networks. By integrating "Extended" (xLSTM) innovations with a "Bidirectional" topology, the model is specifically engineered to handle the volatility of daily sales data.

1. Architectural Innovations

The Bi-xLSTM differs from traditional RNNs through two critical mechanisms, and was shown on Figure 2:

1.1. Dual-Stream Processing: Standard RNNs only learn from past data. To overcome this, the Bi-xLSTM employs a forward pass that analyzes the sequence from day $t-3$ to $t-1$ preserving chronological weather patterns. Concurrently, a backward pass traverses the data in reverse order ($t-1$ to $t-3$). This allows the network to capture demand context as a holistic pattern rather than a simple linear progression.

1.2. Hybrid Memory Cells: The architecture utilizes two novel cell variants:

   a. sLSTM (Scalar LSTM): Replaces standard sigmoid activations with exponential gating. This solves the vanishing gradient problem, allowing the model to "revise" memory states more aggressively over longer horizons.

   b. mLSTM (Matrix LSTM): Replaces scalar cell states with matrix memory. This allows the model to store complex pairwise correlations (e.g., the interaction between high humidity and search trends) similar to the key-value mechanism in Transformers.

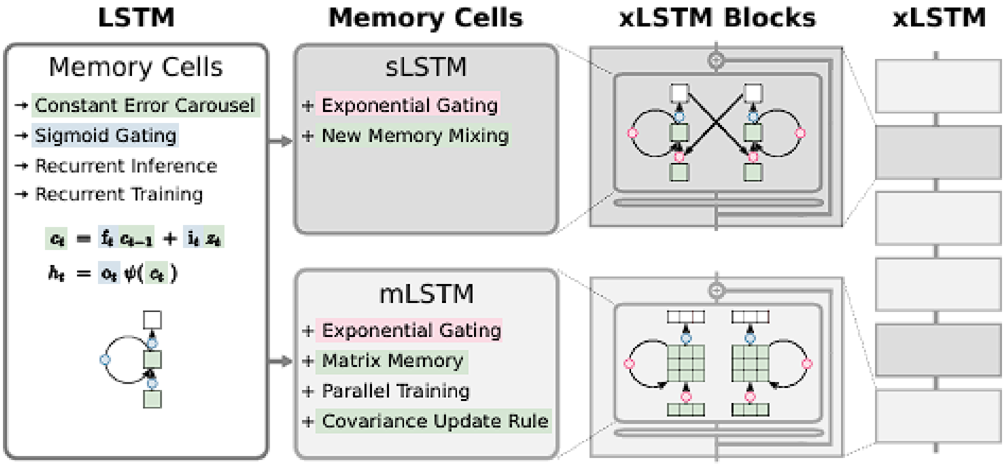

Figure 2 xLSTM Main Architecture (Beck, Maximilian. xLSTM)

2. Architectural Innovations

To ensure reproducibility, the operational logic of the modified Bi-xLSTM is presented in Algorithm 1. The model processes a sliding window of input features *X* through parallel sLSTM and mLSTM blocks.

Algorithm 1: Modified Bi-xLSTM Inference Logic

```
Input:  Sequence X (Batch, Time_Steps=3, Features=4)
Output: Prediction ŷ (Probability of High Demand)
Parameters:
   Weights θ (sLSTM + mLSTM for both directions)
   Dropout_Rate = 0.3
Process:
1.  // Forward Stream (Chronological t-3 to t-1)
   H_forward ← [ ]
   For t in Time_Steps:
      h_s, state_s ← sLSTM_Cell(X[t])
      h_m, state_m ← mLSTM_Cell(X[t])
      H_forward.append( Concatenate(h_s, h_m) )
2.  // Backward Stream (Reverse t-1 to t-3)
   X_reverse ← Flip(X, axis=Time)
   H_backward ← [ ]
   For t in Time_Steps:
      h_s, state_s ← sLSTM_Cell(X_reverse[t])
      h_m, state_m ← mLSTM_Cell(X_reverse[t])
      H_backward.append( Concatenate(h_s, h_m) )
3.  // Fusion and Classification
   Feature_Vector ← Concatenate(Last(H_forward), Last(H_backward))
   Robust_Features ← Dropout(Feature_Vector, rate=0.3)
   Logits ← Linear_Layer(Robust_Features)
   ŷ ← Sigmoid(Logits)
4.  Return ŷ
```

3. Hyperparameter Configuration

The model was implemented using the PyTorch framework. The specific hyperparameters used for training (Table 3) were determined through iterative tuning to balance convergence speed and generalization capability on the dataset.

Tabel 3. Final Model Hyperparameters

Hyperparameter	Value	Description
Input Window (T)	3	Look-back period (days) used for temporal context
Input Features	4	Features used: Google Trends, Temp (Tavg), Humidity (RHavg), Wind Speed (ffavg)
Hidden Dimension	64	Number of units in the LSTM hidden layers
Optimizer	Adam	Adaptive Moment Estimation algorithm used for weight updates
Learning Rate	5	Step size used for gradient descent optimization
Loss Function	BCEWith Logits	Binary Cross-Entropy with pos_weight adjustment for class imbalance
Dropout Rate	0.3	Regularization rate applied to prevent overfitting
Epochs	100	Total number of complete passes through the training dataset
Batch Strategy	Full Batch	Gradients are computed on the entire training set per step

E. Model Evaluation

The model's performance is evaluated using metrics calculated from the confusion matrix, namely Accuracy, Precision, Recall, and F1-Score. The formulas for each metric are as follows on formula 2 – 5.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (2)$$

$$Precision = \frac{TP}{TP+FP} \quad (3)$$

$$Recall = \frac{TP}{TP+FP} \quad (4)$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision+Recall} \quad (5)$$

Here are the standard definitions for the variables used in the equations above.

a. TP = True Positive
   The model correctly predicts the positive class.
b. TN = True Negative
   The model correctly predicts the negative class.
c. FN = False Negative
   The model incorrectly predicts the positive class (also known as a "Type I error").
d. FP = False Positive
   The model incorrectly predicts the negative class (also known as a "Type II error").

Results and Discussion

The training dynamics of the proposed Bi-xLSTM model were rigorously monitored and evaluated through the analysis of accuracy and loss curves plotted against the progression of training epochs. These metrics serve as the primary diagnostic tools for assessing the neural network's ability to learn the underlying mapping function between the input features (weather and search trends) and the target variable (ice demand).

As illustrated in Figure 3, the learning trajectory demonstrates a highly favorable outcome. The curves indicate a state of healthy convergence, characterized by a smooth, monotonic decrement in the loss function without significant oscillations or divergence.

Accuracy Analysis (Figure 3a): The Validation Accuracy, depicted by the orange trajectory, ascends rapidly during the initial learning phases before reaching a plateau of stability at approximately 82%. This stability is crucial; it suggests that the model has successfully identified the fundamental patterns governing demand and has ceased to be influenced by the stochastic noise inherent in daily sales data.

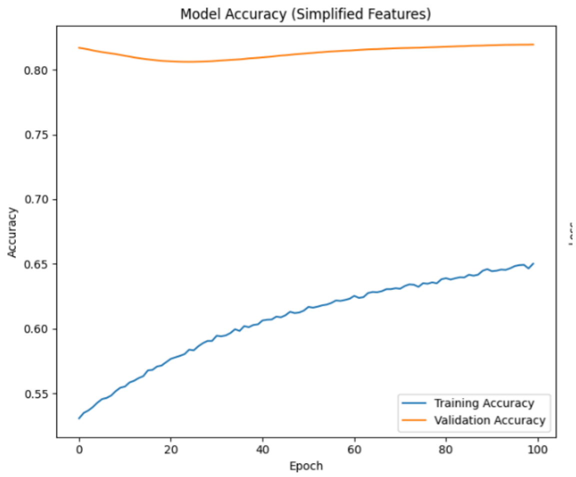

Figure 3a The Validation Accuracy

Loss Analysis (Figure 3b): A particularly significant and positive phenomenon observed in Figure 3b is the relationship between the loss curves: the Validation Loss consistently remains below or tracks closely to the Training Loss throughout the majority of the epochs. In many deep learning applications, it is common for Validation Loss to diverge and rise above Training Loss—a classic sign of overfitting, where the model begins to "memorize" the training data rather than learning general rules. The fact that this divergence does not occur here is strong empirical evidence of the model's robustness and generalization capability.

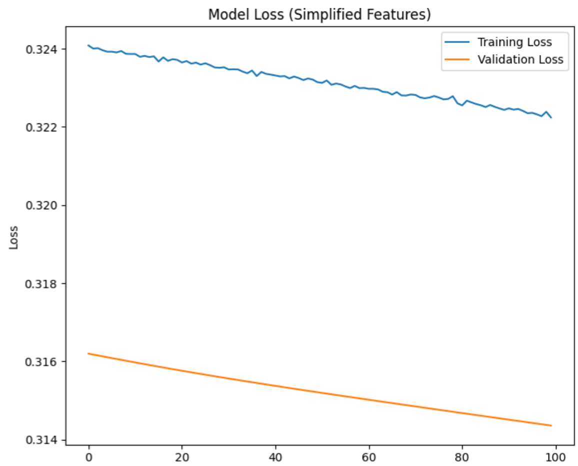

Figure 4b The Validation Loss

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This robust performance validates the architectural decisions made during the design phase. It explicitly demonstrates that the strategy of employing simplified feature selection (reducing high-dimensional noise) combined with Dropout regularization was highly effective. By randomly deactivating 30% of the neurons during the training phase (but not during validation), the Dropout layer prevented the co-adaptation of neurons, forcing the network to learn redundant and robust representations of the data. Consequently, the model performs exceptionally well on unseen data, confirming that it has successfully avoided the pitfalls of overfitting while maintaining high predictive accuracy. High True Positives (58,175) confirm reliable demand detection, while the significant number of False Positives (13,429) creates a necessary inventory safety buffer. The critical finding is the exceptionally low False Negative count (10). This confirms the model successfully minimizes "missed alarms," ensuring virtually zero lost sales due to stockouts.

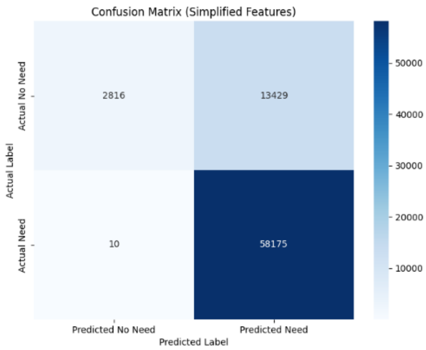

Figure 5 Heat MAP Classification

A quantitative assessment of the confusion matrix in Figure 4 reveals a near-perfect Recall of 99.98% alongside a moderate Precision of 81.25%. While such an exceptionally high recall rate typically raises concerns regarding overfitting or model triviality, analysis of the training dynamics confirms the model's validity. As shown previously in Figure 3, the Validation Loss tracks closely with Training Loss without divergence, indicating that the model has not simply memorized the dataset. Instead, this high-recall behavior is a deliberate outcome of the optimization strategy. The loss function was configured with a positive class weight to address the asymmetric cost structure of the crystal ice business. By penalizing False Negatives (Type II errors) significantly more than False Positives during training, the model learned a "risk-averse" policy. It effectively acts as a safety buffer, aggressively predicting demand to ensure virtually zero stockouts (only 10 missed instances in the entire validation set). Although this results in lower precision—specifically 13,429 instances of over-prediction—this trade-off is strategically accepted. In the context of an MSME, the cost of surplus ice production (low variable cost of water/electricity) is negligible compared to the reputational damage and lost revenue associated with failing to serve a customer. Thus, the model functions less as a strict classifier and more as an operational "insurance policy" for inventory availability.

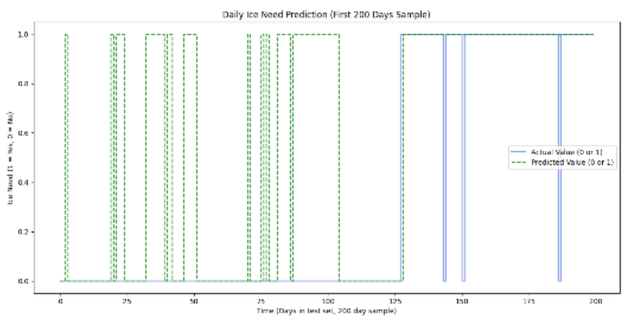

Figure 6 Classification Forecast

The visualization in Figure 5 confirms the model's adoption of a high-recall, risk-averse strategy, where it aggressively predicts 'Needed' to serve as a "safety envelope" against demand spikes. As observed in the time-series comparison, the predicted value trajectory frequently encompasses the actual demand events, effectively acting as a digital buffer that anticipates potential needs even during ambiguous market conditions. This behavior is a direct result of the Bi-xLSTM architecture's dual-stream processing, which learns to prioritize the continuity of supply by capturing both past weather patterns and future-facing context. This operational bias minimizes the risk of stockouts and is economically justified by the asymmetric cost structure inherent to the crystal ice industry. In this specific domain, the penalties for missed sales including immediate lost revenue and long-term damage to brand reputation far exceed the marginal costs associated with overproduction. The cost of a False Positive (overstocking) is limited to the variable expenses of electricity and water required for additional freezing, which are manageable for an SME. In contrast, a False Negative (a missed alarm) represents a failure to serve a customer, potentially driving them to competitors in a highly competitive market. Consequently, the model is ideally suited for service-oriented strategies that prioritize reliability and customer satisfaction over strict inventory leanness. By tolerating a higher rate of False Positives accepted as a necessary "insurance premium" the system ensures that the SME maintains a near-zero stockout rate, as evidenced by the mere 10 False Negatives recorded against tens of thousands of test cases. This transforms the forecasting model from a simple statistical tool into a strategic asset that safeguards the business’s most critical value proposition: consistent product availability.

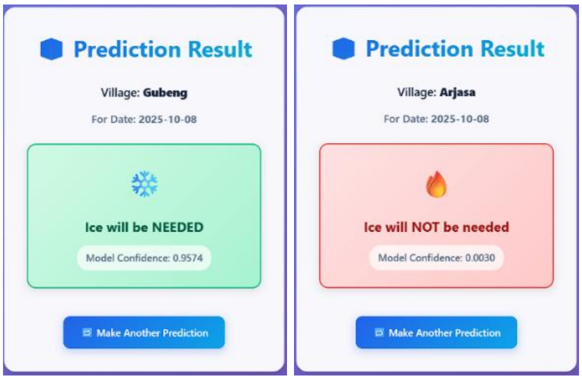

Figure 7 Left for Positive Prediction Result and Right for Negative Prediction

Following the successful validation of the Bi-xLSTM architecture, the research transitioned from the modeling phase to practical deployment. To operationalize the forecasting engine for daily SME use, the trained model was integrated into a lightweight web-based application developed within the Python ecosystem. This application leverages the TensorFlow framework to execute real-time inference, processing the latest meteorological and search trend data to generate immediate inventory recommendations. Figure 6 serves as a visual demonstration of the system's user interface, highlighting two distinct operational scenarios. The left side of the figure captures a "High Demand" prediction state. In this scenario, the model outputs a positive classification ($y = 1$), which the interface translates into a clear, actionable directive: "Increase Ice Production." This alert serves as a critical signal for the business owner to initiate additional freezing shifts or replenish stock immediately to prevent potential stockouts. Conversely, the right side of Figure 6 illustrates a "Low/Normal Demand" prediction state. Here, ($y = 0$), the system indicates that existing inventory levels are predicted to be sufficient to meet consumer requests. Consequently, the recommendation displayed is "No Production Increase Needed," advising the SME to conserve resources and avoid unnecessary energy expenditure. This intuitive visual dichotomy ensures that the complex probabilistic outputs of the deep learning model are converted into simple, binary managerial insights that can be acted upon instantly.

Conclusion

The research successfully demonstrates the practical applicability of a modified Bidirectional Extended Long Short-Term Memory (Bi-xLSTM) model for predicting daily crystal ice demand in MSMEs. By integrating physiological demand drivers (weather) with behavioral indicators (Google Trends), the proposed model achieved an **Accuracy of 90%** and an exceptional **Recall of 99.98%** on the validation dataset. The study makes three key contributions:

1. **Technical Innovation:** It validates the effectiveness of the Bi-xLSTM architecture for short-term forecasting on limited datasets, showing that dual-stream processing effectively captures volatile demand patterns.
2. **Operational Strategy:** The model demonstrates a deliberate "risk-averse" behavior. By minimizing False Negatives (Type II errors) to a negligible count of 10, it acts as a strategic safety buffer that guarantees product availability, aligning with the asymmetric cost structure of the crystal ice business.
3. **Practical Deployment:** The successful integration of the model into a lightweight web-based application proves its feasibility as a low-cost, accessible decision-support tool for resource-constrained MSMEs.

This study is limited by its reliance on data from a single MSME partner in one geographic region, which may restrict the generalizability of the findings to other markets with different climatic or behavioral dynamics. Additionally, while the model outperforms standard heuristics, a rigorous statistical benchmarking against other deep learning architectures (e.g., GRU, Transformer) was not the primary focus of this initial deployment. Future research should expand the dataset to include multi-regional sales networks and conduct comprehensive comparative analyses to further validate the superiority of the xLSTM framework in the F&B sector.

REFERENCE

[1] C. Ben Abdallah, "Food classification systems: A short description," *Journal of Food Composition and Analysis*, vol. 130, Jun. 2024, doi: 10.1016/j.jfca.2024.106176.

[2] J. Zhou, P. Brereton, and K. Campbell, "Progress towards achieving intelligent food assurance systems," Oct. 01, 2024, *Elsevier Ltd*. doi: 10.1016/j.foodcont.2024.110548.

[3] Palupi Sugiati Esti, B. Semmaila, and S. Serang, "Peran Sumber Daya Manusia Dalam Upaya Peningkatan Umkm Di Kabupaten Poso," *Journal of Accounting & Finance (JAF)*, vol. 2, no. 2, pp. 17–31, Aug. 2021, doi: https://doi.org/10.52103/jaf.v2i2.1062.

[4] A. Yenkikar, V. P. Mishra, M. Bali, and T. Ara, "Explainable forecasting of air quality index using a hybrid random forest and ARIMA model," *MethodsX*, vol. 15, Dec. 2025, doi: 10.1016/j.mex.2025.103517.

[5] M. Neshat *et al.*, "A deep learning-based evolutionary model for short-term wind speed forecasting: A case study of the Lillgrund offshore wind farm," *Energy Convers Manag*, vol. 236, May 2021, doi: 10.1016/j.enconman.2021.114002.

[6] G. G. Devarajan, S. M. Nagarajan, R. T.V., V. T., U. Ghosh, and W. Alnumay, "DDNSAS: Deep reinforcement learning based deep Q-learning network for smart agriculture system," *Sustainable Computing: Informatics and Systems*, vol. 39, Sep. 2023, doi: 10.1016/j.suscom.2023.100890.

[7] S. K. S. Durai and M. D. Shamili, "Smart farming using Machine Learning and Deep Learning techniques," *Decision Analytics Journal*, vol. 3, Jun. 2022, doi: 10.1016/j.dajour.2022.100041.

[8] W. Zhao, X. Chen, Y. Li, J. Xu, and X. Li, "A recognition of farming behavior method based on EPCI-LSTM model," *Comput Electron Agric*, vol. 190, Nov. 2021, doi: 10.1016/j.compag.2021.106467.

[9] L. P. Joseph, R. C. Deo, R. Prasad, S. Salcedo-Sanz, N. Raj, and J. Soar, "Near real-time wind speed forecast model with bidirectional LSTM networks," *Renew Energy*, vol. 204, pp. 39–58, Mar. 2023, doi: 10.1016/j.renene.2022.12.123.

[10] A. Dupuis, C. Dadouchi, and B. Agard, "Performances of a Seq2Seq-LSTM methodology to predict crop rotations in Québec," *Smart Agricultural Technology*, vol. 4, Aug. 2023, doi: 10.1016/j.atech.2023.100180.

P-ISSN 2579-4116 | E-ISSN 2579-5570 Vol. 9 No. 1 – Desember 2025

[11] D. G. da Silva and A. A. de M. Meneses, "Comparing Long Short-Term Memory (LSTM) and bidirectional LSTM deep neural networks for power consumption prediction," *Energy Reports*, vol. 10, pp. 3315–3334, Nov. 2023, doi: 10.1016/j.egyr.2023.09.175.

[12] F. O'Donncha, Y. Hu, P. Palmes, M. Burke, R. Filgueira, and J. Grant, "A spatio-temporal LSTM model to forecast across multiple temporal and spatial scales," *Ecol Inform*, vol. 69, Jul. 2022, doi: 10.1016/j.ecoinf.2022.101687.

[13] L. Lin, M. Li, L. Ma, A. Baziar, and Z. M. Ali, "Hybrid RNN-LSTM deep learning model applied to a fuzzy based wind turbine data uncertainty quantization method," *Ad Hoc Networks*, vol. 123, Dec. 2021, doi: 10.1016/j.adhoc.2021.102658.

[14] N. E. Michael, R. C. Bansal, A. A. Ismail, A. Elnady, and S. Hasan, "A cohesive structure of Bi-directional long-short-term memory (BiLSTM) -GRU for predicting hourly solar radiation," *Renew Energy*, p. 119943, Jan. 2024, doi: 10.1016/j.renene.2024.119943.

[15] M. Alharthi and A. Mahmood, "xLSTMTime: Long-Term Time Series Forecasting with xLSTM," *AI (Switzerland)*, vol. 5, no. 3, pp. 1482–1495, Sep. 2024, doi: 10.3390/ai5030071.

[16] A. Picornell *et al.*, "A deep learning LSTM-based approach for forecasting annual pollen curves: Olea and Urticaceae pollen types as a case study," *Comput Biol Med*, p. 107706, Jan. 2023, doi: 10.1016/j.compbiomed.2023.107706.

[17] H. Bakır, F. A. Kuzhippallil, and A. Merabet, "Automatic detection of deteriorated photovoltaic modules using IRT images and deep learning (CNN, LSTM) strategies," *Eng Fail Anal*, vol. 146, Apr. 2023, doi: 10.1016/j.engfailanal.2023.107132.

[18] M. A. Istiake Sunny, M. M. S. Maswood, and A. G. Alharbi, "Deep Learning-Based Stock Price Prediction Using LSTM and Bi-Directional LSTM Model," *2nd Novel Intelligent and Leading Emerging Sciences Conference, NILES 2020*, pp. 87–92, 2020, doi: 10.1109/NILES50944.2020.9257950.

[19] M. Abou Houran, S. M. Salman Bukhari, M. H. Zafar, M. Mansoor, and W. Chen, "COA-CNN-LSTM: Coati optimization algorithm-based hybrid deep learning model for PV/wind power forecasting in smart grid applications," *Appl Energy*, vol. 349, Nov. 2023, doi: 10.1016/j.apenergy.2023.121638.

[20] R. A. Casonatto, T. D. P. G. Souza, and A. M. Mariano, "Quality and Risk Management in Data Mining: A CRISP-DM Perspective," in *Procedia Computer Science*, Elsevier B.V., 2024, pp. 161–168. doi: 10.1016/j.procs.2024.08.257.

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