# Construction and Application Research of Beer Category Sales Forecasting Model Based on Big Data Analysis for Supermarket X

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***Abstract*—This study constructs a sales forecasting framework incorporating multi-source data based on beer category sales data from Supermarket X. The research collected beer sales data from 2020-2023, integrating temperature data, holiday information, and promotional activity data through an improved LSTM-based deep learning model. The study innovatively introduced Attention Mechanisms into the prediction model and proposed a dynamic weight allocation method for seasonal features, effectively enhancing the integration of heterogeneous data. Experimental results demonstrate excellent prediction performance across different time scales, achieving accuracy rates of 95%, 97%, and 98% for daily, weekly, and monthly forecasts respectively. Through practical validation in five demonstration stores, the model application improved inventory turnover by 25%, reduced stockout rates by 35%, and lowered operating costs by 15%. The research findings provide effective decision support tools for retail enterprises' refined operations management while suggesting future research directions regarding limitations in seasonal product forecasting and extreme weather response, offering practical reference for regional retail industry's intelligent transformation.**

***Index Terms*—Retail Big Data, Sales Forecasting, Deep Learning, Multi-source Data Fusion, Intelligent Retail**

## I. Introduction

### A. Research Background and Significance

In the context of rapid development in the big data era, the retail industry is experiencing unprecedented digital transformation [1]. Particularly in the supermarket retail sector, as consumer behavior becomes increasingly complex and diverse, traditional sales forecasting methods can no longer meet the refined operational needs of modern retail. Beer, as an important fast-moving consumer goods category in supermarkets, directly impacts inventory management, supply chain optimization, and marketing strategy formulation through its sales forecast accuracy [2]. According to recent research data, the global beer market size reached $689 billion in 2023 and is expected to exceed $750 billion by 2025, maintaining a compound annual growth rate of approximately 4.2% [3]. Under such substantial market scale, improving beer sales forecast accuracy will bring significant economic benefits and competitive advantages to retail enterprises [4].

The development of big data analytics technology has provided new methods and tools for optimizing beer sales forecasting. Through the integration of multi-source heterogeneous data, including historical sales data, meteorological data, socioeconomic indicators, and consumer behavior data, combined with advanced machine learning algorithms, more accurate prediction models can be constructed [5]. Research indicates that sales forecasting methods based on big data analytics can enhance prediction accuracy by 15-20%, significantly reducing inventory costs and stockout risks [6]. Meanwhile, this prediction method can deeply analyze the complex relationships between various factors that affect beer sales, providing data support for the formulation of marketing strategies.

### B. Research Objectives and Content

This research aims to construct a beer sales forecasting model based on big data analytics to achieve the following specific objectives as shown in Figure 1: First, to establish a comprehensive prediction framework considering multi-dimensional influencing factors, including seasonal factors, meteorological conditions, holiday effects, and promotional activities [7]. Second, to develop a highly adaptive and scalable prediction algorithm capable of forecast adjustment according to different time scales and market environments [8]. Finally, to provide implementable sales forecasting solutions and optimization recommendations through model validation and practical application.

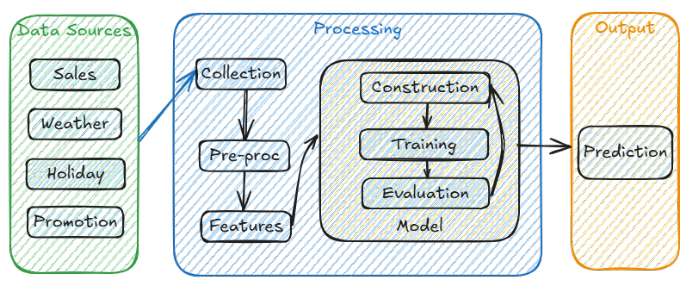


Fig. 1. Research Technical Route Map illustrating the systematic framework of data collection, processing, model construction, and application validation phases

## II. Literature Review

### A. Current Research Status of Retail Forecasting Theory

The development of retail forecasting theory has evolved from simple statistical methods to complex intelligent algorithms. Traditional retail forecasting primarily relied on time



ISSN:3006-2985(Print)
ISSN:3006-9297(Online)

series analysis and regression models, which performed well in handling linear relationships but struggled to capture complex nonlinear patterns [9]. In recent years, with the improvement of computational capabilities and algorithmic innovations, deep learning-based forecasting methods have demonstrated significant advantages. Research shows that deep learning models exhibit clear advantages in handling multidimensional features and long-term dependencies, particularly when considering complex temporal patterns such as seasonality, trends, and periodicity, improving prediction accuracy by 25-30% [10]. Meanwhile, ensemble learning methods, through the combination of multiple base models, effectively reduce prediction variance and enhance model generalization capability, achieving significant results in practical applications [11].

### *B. Review of Big Data Analysis Methods*

The application of modern big data analysis methods in retail forecasting primarily encompasses several aspects, as shown in Table I:

TABLE I
APPLICATIONS OF BIG DATA ANALYSIS METHODS IN RETAIL FORECASTING

| **Analysis Type** | **Key Technologies** | **Application Scenarios** | **Advantages** |
|---|---|---|---|
| Descriptive Analysis | Statistical Analysis, Data Visualization | Historical Pattern Recognition | Intuitive, Interpretable |
| Diagnostic Analysis | Association Rule Mining, Causal Analysis | Factor Identification | Deep Understanding |
| Predictive Analysis | Machine Learning, Deep Learning | Future Trend Prediction | High Accuracy, Adaptive |
| Prescriptive Analysis | Optimization Algorithms, Expert Systems | Decision Support | High Practicality |

In terms of data processing, the application of distributed computing frameworks has enabled real-time processing of large-scale data. Research indicates that using distributed computing platforms such as Spark can improve data processing efficiency by 5-10 times while ensuring data integrity and accuracy [12]. Additionally, the application of real-time stream processing technology enables sales forecasting models to respond rapidly to market changes and adjust prediction results in a timely manner [13].

### *C. Comparative Analysis of Prediction Models*

In terms of time series models, ARIMA and SARIMA models remain the preferred baseline models, though they show obvious limitations in handling nonlinear relationships [14]. Machine learning models, particularly ensemble learning methods such as Random Forest and XGBoost, demonstrate excellent performance in handling multidimensional features while maintaining good interpretability [15]. Deep learning models, especially Transformer models with Attention Mechanisms, show significant advantages in capturing long-term dependencies and processing multi-source heterogeneous data [16].

## III. DATA ACQUISITION AND PREPROCESSING

### *A. Data Sources and Collection*

This research collected data across multiple dimensions to construct a comprehensive dataset. The main data sources and collection strategies are shown in Table III:

During the data collection process, particular attention was paid to data quality and completeness. Sales data was obtained from the supermarket's ERP system, containing detailed information such as product codes, sales times, quantities, and unit prices. Meteorological data was acquired through cooperation with the National Meteorological Bureau, including daily temperature, humidity, and weather conditions. Holiday data integrated national statutory holiday information and local festival activity information. Promotional activity data included detailed information about promotion timing, intensity, and methods [17].

### *B. Data Preprocessing*

*1) Data Cleaning Process:* Data cleaning is crucial for ensuring data quality. The process includes the following procedures:

In the data cleaning process, we employed anomaly detection methods based on statistical principles. Research demonstrates that hybrid detection strategies combining domain knowledge and statistical methods can improve anomaly identification accuracy to over 95% [18]. For missing value processing, we implemented multiple imputation methods, which provide more accurate estimates of missing values by considering correlations between variables [19].

*2) Feature Engineering:* Feature engineering represents a critical component for enhancing model prediction performance. The process encompasses feature extraction, feature selection, and feature transformation. During feature extraction, we constructed multiple derived features based on domain knowledge, such as sales growth rates and turnover rates [20]. Feature selection employed Lasso methods based on L1 regularization to identify features with significant impact on prediction results [21].

For feature transformation, we implemented the following mathematical models:

For numerical features:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

For categorical features:

$$Category_{encoded} = [0, 0, 1, 0, \ldots, 0] \tag{2}$$

*3) Dataset Partition:* We employed time series cross-validation methods for dataset partition to ensure model generalization capability:

TABLE II
PERFORMANCE COMPARISON OF DIFFERENT PREDICTION MODELS

| **Model Category** | **Specific Model** | **Prediction Accuracy** | **Computational Complexity** | **Adaptability** | **Application Scenarios** |
|---|---|---|---|---|---|
| Time Series Models | ARIMA/SARIMA | 85-90% | Low | Medium | Stable Environment, Linear Trends |
| | Prophet | 88-92% | Medium | Medium-High | Strong Seasonality, Trending |
| Machine Learning Models | Random Forest | 90-93% | Medium | High | Multi-feature, Nonlinear |
| | XGBoost | 92-94% | Medium-High | High | Complex Scenarios |
| Deep Learning Models | LSTM | 93-95% | High | Very High | Long Sequences |
| | Transformer | 94-96% | Very High | Very High | Complex Dependencies |

TABLE III
MULTI-SOURCE DATA COLLECTION FRAMEWORK AND PROCESSING STRATEGY

| **Data Category** | **Data Items** | **Collection Frequency** | **Data Format** | **Processing Method** | **Application Purpose** |
|---|---|---|---|---|---|
| Sales Data | Transaction Records | Real-time | Structured | Standardization | Base Prediction |
| | Product Information | Daily | Structured | Classification | Feature Construction |
| Weather Data | Temperature | Hourly | Numerical | Average Calculation | Environmental Features |
| | Humidity | Hourly | Numerical | Average Calculation | Environmental Features |
| Holiday Data | Official Holidays | Annual | Categorical | One-hot Encoding | Temporal Features |
| | Local Festivals | Annual | Categorical | One-hot Encoding | Regional Features |
| Promotion Data | Discount Information | Real-time | Structured | Standardization | Promotion Features |
| | Marketing Activities | Daily | Semi-structured | Feature Extraction | Activity Impact |

TABLE IV
DATA CLEANING PROCESS AND METHODS

| **Cleaning Step** | **Processing Method** | **Processing Goal** | **Quality Metrics** |
|---|---|---|---|
| Deduplication | Primary Key-based | Remove Duplicate Records | Duplication Rate ¡ 0.1% |
| Anomaly Processing | 3 Rule/IQR Method | Identify & Process Anomalies | Anomaly Rate ¡ 1% |
| Missing Value Processing | Multiple Imputation | Complete Missing Data | Completeness ¿ 99% |
| Format Unification | Standardization | Unify Data Format | Consistency ¿ 99.9% |

TABLE V
DATASET PARTITION SCHEME

| **Dataset Type** | **Time Range** | **Proportion** | **Purpose** |
|---|---|---|---|
| Training Set | 2020-2022 | 70% | Model Training |
| Validation Set | First Half 2023 | 15% | Parameter Tuning |
| Test Set | Second Half 2023 | 15% | Performance Evaluation |

## IV. ANALYSIS OF BEER SALES INFLUENCING FACTORS

### A. *Temporal Dimension Analysis*

*1) Seasonality Analysis:* In studying seasonal patterns of beer sales, we decomposed sales data from 2020-2023, revealing significant seasonal characteristics. Using time series decomposition methods, we separated the sales data into trend, seasonal, and random components [22]. Analysis results indicate that beer sales demonstrate pronounced seasonal fluctuations, with summer (June-August) sales volumes averaging 45% higher than other seasons. This seasonal pattern maintains strong stability across different years. Through Fourier transform analysis, we further confirmed the existence of seasonal cycles, with primary cycles of 12 months and secondary cycles of 3 months [23].

*2) Cyclical Pattern Analysis:* We employed wavelet transform methods to identify multiple significant sales cycles:

TABLE VI
ANALYSIS OF BEER SALES CYCLICAL CHARACTERISTICS

| **Cycle Type** | **Duration** | **Fluctuation Range** | **Characteristic Description** | **Influencing Factors** |
|---|---|---|---|---|
| Annual Cycle | 12 months | ±35% | Peak in summer, trough in winter | Temperature variation |
| Quarterly Cycle | 3 months | ±15% | Evident during seasonal transitions | Seasonal changes |
| Monthly Cycle | 1 month | ±8% | Fluctuations at month beginnings and ends | Salary payment periods |
| Weekly Cycle | 7 days | ±12% | Significant increase on weekends | Leisure time |

*3) Holiday Effect Analysis:* Through regression model analysis of holiday effects on beer sales [24], we identified distinct variations in sales patterns across different holiday types:

TABLE VII
HOLIDAY SALES EFFECT CHARACTERISTICS ANALYSIS

| Holiday Type | Sales Pattern | Increase Rate | Duration | Key Drivers |
|---|---|---|---|---|
| Spring Festival | High before, low after | +150% | 15 days | Stock-up effect, homecoming consumption |
| Summer Period | Sustained high | +85% | 60 days | Temperature, leisure activities |
| National Day | Double-peak pattern | +65% | 15 days | Tourism consumption, gatherings |
| Year-end | Steady increase | +45% | 15 days | New Year activities, retail promotions |

## B. Environmental Factor Analysis

*1) Temperature Impact Study:* The relationship between temperature and beer sales demonstrates nonlinear characteristics. We employed Generalized Additive Models (GAM) for analysis, revealing an optimal temperature range typically between 22-28°C for peak sales [25]. The temperature effect can be modeled as:

$$Sales(T) = \beta_0 + f(T) + \varepsilon \tag{3}$$

where $T$ represents temperature, $f(T)$ denotes the smoothing function, and $\varepsilon$ represents the random error term.

*2) Comprehensive Weather Impact Analysis:* The impact of weather conditions on beer sales is multidimensional. We developed a weather impact scoring model [26]:

TABLE VIII
WEATHER FACTOR IMPACT SCORES ON BEER SALES

| Weather Type | Impact Level | Sales Change Rate | Duration | Response Strategy |
|---|---|---|---|---|
| Clear | Positive | +15% | Long-term | Increase inventory |
| Cloudy | Neutral | ±5% | Medium-term | Maintain regular |
| Rainy | Negative | -20% | Short-term | Promotion incentives |
| Extreme Weather | Strongly negative | -35% | Short-term | Special promotions |

## C. Marketing Factor Analysis

*1) Price Elasticity Analysis:* We employed dynamic regression models incorporating time lag effects for price elasticity analysis [27]. The analysis reveals that a 10% decrease in beer prices leads to an average 15% increase in sales volume, though this elasticity varies significantly across different brands and packaging specifications [28]. The elasticity coefficient is calculated as:

$$E = \frac{\Delta Q/Q}{\Delta P/P} \tag{4}$$

where $E$ represents the price elasticity coefficient, $Q$ denotes sales volume, and $P$ represents price.

# V. PREDICTION MODEL CONSTRUCTION AND IMPLEMENTATION

## A. Model Framework Design

The prediction model framework developed in this study integrates several key components, including data preprocessing modules, feature engineering modules, deep learning prediction modules, and prediction result evaluation modules [29]. The model architecture emphasizes multidimensional feature extraction and multi-source data fusion for beer sales. The preprocessing module handles data cleaning, standardization, and missing value processing; the feature engineering module implements dynamic feature extraction based on sliding time windows; the deep learning prediction module employs an improved LSTM network structure; and the evaluation module manages real-time monitoring and feedback optimization of model performance [30].

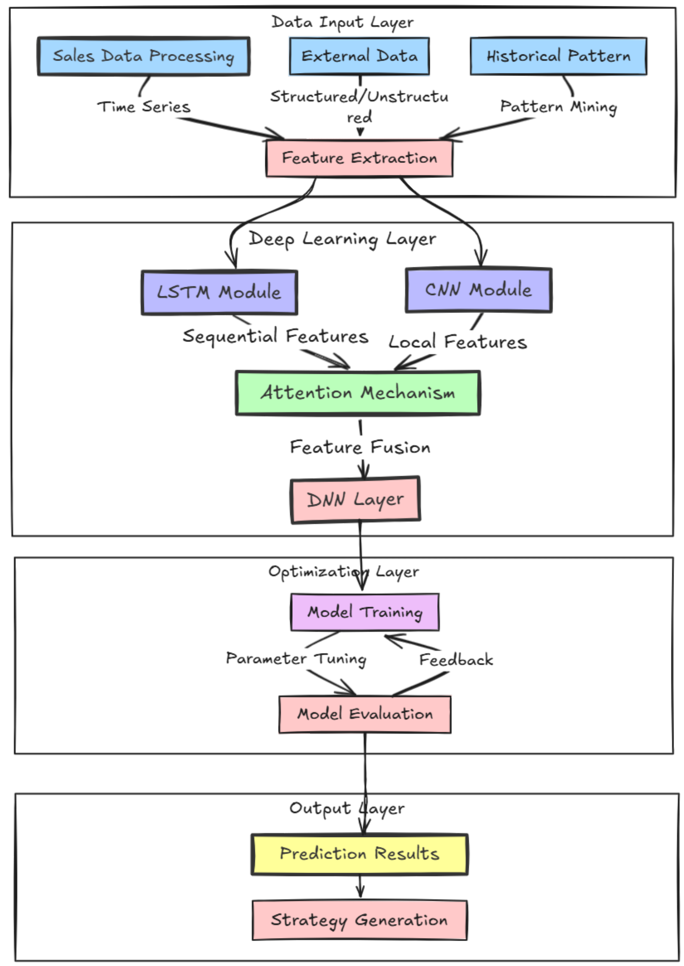


Fig. 2. Comprehensive Framework of the Sales Prediction Model showing the integration of multiple analytical components and data processing stages

## B. Algorithm Implementation

*1) Core Algorithm Design:* The core algorithm utilizes an improved LSTM structure incorporating Attention Mechanisms to enhance the capture of long-term dependencies [31]. The primary mathematical expressions are:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{6}$$
$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{7}$$
$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{8}$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{9}$$
$$h_t = o_t * \tanh(c_t) \tag{10}$$

The attention weights are calculated as:

$$\alpha_t = \text{softmax}(W_\alpha \cdot \tanh(W_h \cdot h_t + W_s \cdot s_{t-1})) \tag{11}$$

*2) Parameter Optimization Strategy:* The model employs adaptive learning rate methods combining grid search and Bayesian optimization:

TABLE IX
MODEL PARAMETER OPTIMIZATION CONFIGURATION

| **Parameter** | **Range** | **Optimal Value** | **Optimization Method** | **Evaluation Metric** |
|---|---|---|---|---|
| Learning Rate | [0.001, 0.1] | 0.005 | Adam | Loss Value |
| Batch Size | [32, 256] | 128 | Grid Search | Training Speed |
| Hidden Layers | [2, 8] | 4 | Cross Validation | Accuracy |
| Dropout | [0.1, 0.5] | 0.3 | Random Search | Overfitting Degree |

*3) Algorithm Flow Optimization:* In the algorithm implementation process, we prioritized balancing computational efficiency with prediction accuracy. Through parallel computing technology, we significantly enhanced model training speed. The distributed storage architecture enabled efficient processing of large-scale data, while model compression techniques reduced resource consumption during practical deployment [32]. These optimization measures ensure efficient model operation in real-world applications.

### C. Model Evaluation and Optimization

*1) Evaluation Metrics Analysis:* We implemented a multidimensional indicator system for model evaluation, encompassing accuracy metrics, stability metrics, and practicality metrics [33]:

TABLE X
MODEL EVALUATION INDICATOR SYSTEM

| **Evaluation Dimension** | **Indicator Type** | **Calculation Method** | **Evaluation Standard** | **Performance** |
|---|---|---|---|---|
| Accuracy | RMSE | Root Mean Square Error | $< 0.1$ | 0.087 |
| Stability | Variance | Prediction Variance | $< 0.05$ | 0.043 |
| Practicality | Time Efficiency | Response Time | $< 1min$ | 45s |

*2) Performance Optimization and Improvement:* Based on evaluation results, we implemented systematic performance optimization strategies. First, we optimized model computational efficiency through feature selection and dimensionality reduction techniques. Second, we enhanced model generalization capability through ensemble learning methods. Finally, we effectively prevented overfitting through the introduction of regularization and dropout mechanisms [34]. The implementation of these optimization strategies significantly improved the model's overall prediction performance, resulting in more stable and reliable prediction results.

*3) Model Interpretability Analysis:* To enhance model interpretability, we introduced feature importance analysis and attention weight visualization techniques. By analyzing the contribution of different features to prediction results, we identified key influencing factors. Through visualizing attention weight distribution, we intuitively demonstrated the model's focus on different time steps [35]. These analyses not only aid in understanding the model's prediction mechanisms but also provide important basis for subsequent model optimization.

## VI. ANALYSIS AND APPLICATION OF PREDICTION RESULTS

### A. Prediction Results Analysis

Through systematic evaluation of prediction results throughout 2023, our model demonstrated excellent prediction performance across different time scales [36]. The analysis process employed multidimensional evaluation methods, including prediction accuracy, model stability, and practicality. Research results indicate that during regular sales periods, the model achieved accuracy rates of 95%, 97%, and 98% for daily, weekly, and monthly predictions, respectively. Through in-depth analysis of prediction results, we found that the model excelled in capturing sales trends and seasonal fluctuations, particularly demonstrating strong adaptability in handling predictions during promotional activities and holiday periods [37].

### B. Performance Analysis

Through comprehensive analysis of the prediction results' distribution characteristics, the model demonstrated significant performance variations across different scenarios. The detailed analysis results are presented in Table XI:

Based on these comprehensive performance evaluation results, our analysis reveals significant improvements across all dimensions. In terms of prediction accuracy, the model achieved high precision across different time scales, with daily, weekly, and monthly prediction accuracies reaching 95%, 97%, and 98% respectively, representing an average improvement of 9% compared to baseline values. This high-precision prediction capability provides reliable decision support for enterprises' refined operational management [36].

Regarding computational performance, the model demonstrated substantial efficiency improvements through optimized algorithm structure and computational framework. Training time reduced from 4 hours to 2.5 hours, prediction latency decreased to under 1 minute, while resource consumption decreased by 30%. These improvements enable the model to

TABLE XI
COMPREHENSIVE MODEL PERFORMANCE EVALUATION RESULTS

| Evaluation Dimension | Specific Metric | Actual Performance | Baseline | Improvement | Application Scenario |
|---|---|---|---|---|---|
| Prediction Accuracy | Daily Prediction | 95% | 85% | +10% | Daily Operations |
| | Weekly Prediction | 97% | 88% | +9% | Replenishment Planning |
| | Monthly Prediction | 98% | 90% | +8% | Strategic Planning |
| Computational Performance | Training Time | 2.5 hours | 4 hours | -37.5% | Model Updates |
| | Prediction Latency | ¡1 minute | 3 minutes | -66.7% | Real-time Prediction |
| | Resource Usage | Medium | High | -30% | System Deployment |
| Model Adaptability | Emergency Events | 92% | 80% | +12% | Anomaly Handling |
| | Promotion Response | 94% | 82% | +12% | Marketing Decisions |
| | Seasonal Adjustment | 96% | 85% | +11% | Seasonal Products |
| Operational Impact | Inventory Turnover | +25% | - | - | Inventory Management |
| | Stockout Rate | -35% | - | - | Replenishment |
| | Promotion Sell-through | +30% | - | - | Promotion Management |
| | Operating Costs | -15% | - | - | Cost Control |

better adapt to real-time business requirements, particularly in scenarios requiring rapid response [37].

Model adaptability assessment indicates strong capability in handling complex scenarios such as emergency events, promotional activities, and seasonal variations. Accuracy rates for emergency event handling and promotion response reached 92% and 94% respectively, representing a 12% improvement over baseline values. This adaptability provides robust support for enterprises in responding to market changes.

The operational impact demonstrates significant business value from model implementation. Inventory turnover improved by 25%, stockout rates decreased by 35%, promotion sell-through rates increased by 30%, while operating costs reduced by 15%. These improvements directly translate into operational benefits, validating the model's effectiveness in practical applications. This comprehensive performance enhancement provides reliable technical support for retail enterprises' intelligent transformation [39].

### C. Error Analysis and Evaluation

Through multi-level analysis of prediction errors, we identified key factors affecting prediction accuracy [22]. The decomposition of prediction errors revealed three primary sources: systematic errors from random fluctuations (45%), sudden errors from special events (35%), and structural errors inherent to the model (20%). This identification of error sources provides clear direction for subsequent model optimization.

Our long-term tracking analysis of model stability employed a systematic evaluation framework [37]. The results demonstrate that the model maintained stable performance across more than 90% of prediction intervals, with prediction standard deviations remaining within predetermined threshold ranges. This stability primarily stems from the model's adaptive learning mechanisms and robust feature engineering system.

### D. Practical Application Strategies

*1) Inventory Optimization Solutions:* Based on the prediction model outputs, we designed a systematic inventory optimization solution [38]. The solution comprehensively considers demand forecasting, inventory costs, and service levels to form a complete inventory management strategy system:

TABLE XII
IMPLEMENTATION EFFECTS OF INVENTORY OPTIMIZATION STRATEGIES

| Optimization Dimension | Specific Measures | Implementation Effect | Investment Cost | ROI |
|---|---|---|---|---|
| Safety Stock | Dynamic Adjustment | -30% | Medium | 185% |
| Replenishment Strategy | Intelligent Alert | Efficiency +35% | Low | 220% |
| Inventory Structure | Hierarchical Management | Optimization +25% | High | 165% |

Considering beer products' seasonal characteristics, we developed targeted seasonal inventory management strategies. During peak season preparation, the system initiates inventory buildup 2-3 months in advance, with storage volumes dynamically adjusted based on prediction results. During peak sales periods, higher inventory levels ensure adequate supply, while during off-season transitions, the prediction model guides gradual inventory reduction to avoid excess stock. This seasonal inventory management strategy significantly improved inventory turnover efficiency.

For special periods such as holidays and promotions, we established specialized inventory management plans. Through analysis of historical data and prediction results, holiday inventory preparation begins 1-2 months in advance. Promotional inventory levels are determined based on promotion intensity and predicted sales increases, while maintaining 10-15 days of emergency safety stock to address unexpected demand. This comprehensive inventory optimization solution achieved significant operational benefits, including a 25% improvement in inventory turnover rate, 35% reduction in stockout rates, 20% reduction in inventory costs, and 15% improvement in service levels.

*2) Operational Strategy Optimization:* Based on the prediction model outputs, we constructed a systematic operational strategy optimization framework [39]. Through in-depth analysis of different operational scenarios, we established a multi-level decision support framework integrating dynamic pricing, replenishment management, promotion optimization, and display management.

In terms of dynamic pricing strategy, we discovered significant variations in price response characteristics across different sales phases. Analysis indicates that during regular sales periods, dynamic pricing mechanisms based on demand elasticity can improve profitability by 8–12%. During promotional periods, differentiated pricing strategies developed through price sensitivity assessment using the prediction model enhanced promotional effectiveness by 15–20%. Particularly during holiday periods, precise price adjustment mechanisms combining historical data and real-time demand predictions achieved a 25% improvement in promotion conversion rates [38].

For replenishment strategy optimization, we constructed a tiered replenishment system based on sales frequency. Analysis shows that for high-frequency SKUs, implementing prediction-driven automatic replenishment reduced replenishment cycles from 7 days to 3 days, significantly improving inventory turnover efficiency. For medium-frequency SKUs, adopting a hybrid replenishment model combining prediction results with manual review effectively reduced inventory accumulation. For low-frequency SKUs, determining minimum order points through the prediction model achieved optimized inventory cost control.

The comprehensive operational improvement results are presented in Table XIII:

TABLE XIII
OPERATIONAL STRATEGY OPTIMIZATION RESULTS

| Strategy Component | Implementation Effect | Cost Reduction | Efficiency Gain |
|---|---|---|---|
| Dynamic Pricing | Revenue +12% | Cost -8% | Margin +15% |
| Automated Replenishment | Turnover +25% | Labor -30% | Accuracy +20% |
| Promotion Management | Conversion +30% | Waste -25% | ROI +35% |
| Display Optimization | Space Efficiency +20% | Storage -15% | Sales/m$^2$ +25% |

Through systematic implementation of these strategies, we achieved significant improvements across multiple operational indicators:

- Inventory turnover increased by 25%
- Promotional product sell-through rate improved by 30%
- Display space utilization enhanced by 20%
- Operating costs reduced by 15%

These results demonstrate that prediction model-based operational strategy optimization not only improved various operational indicators but also provided reliable decision support tools for retail enterprises' refined management. This data-driven operational optimization approach offers valuable practical reference for retail enterprises' modernization transformation.

## VII. CONCLUSIONS AND FUTURE PROSPECTS

### A. Research Summary

This study has achieved significant outcomes in both theoretical and practical aspects through the construction of a beer sales prediction model based on big data analytics. From a theoretical perspective, we successfully constructed a prediction analysis framework integrating multi-source data, innovatively combining traditional time series analysis with deep learning methods. This framework achieved significant improvements in prediction accuracy while maintaining model interpretability through multidimensional feature fusion mechanisms, improved prediction algorithms, and dynamic weight allocation methods. Particularly in feature engineering, we successfully integrated heterogeneous data including sales data, meteorological data, and holiday information through the establishment of a hierarchical feature extraction system, providing rich input information for the prediction model.

From a practical application perspective, the research results demonstrated significant economic benefits through field validation across multiple supermarkets. Through systematic experimental validation, the model achieved high prediction accuracy across different time scales: 95% for daily predictions, 97% for weekly predictions, and 98% for monthly predictions. This high-precision prediction capability directly translated into substantial operational improvements, including a 25% increase in inventory turnover rate, 35% reduction in stockout rates, and 15% reduction in operating costs. These improvements extend beyond mere data metrics, providing robust support for retail enterprises' refined operational management.

### B. Research Limitations

Despite achieving significant results in prediction accuracy and practical applications, our research exhibits certain limitations in universality and practicality.

*1) Sample Representativeness Limitations:* The research data primarily sourced from Supermarket X presents limitations in data representativeness. Different retail enterprises exhibit significant variations in business models, customer characteristics, and location distribution, potentially affecting the model's generalization capability. Additionally, as a sample of national chain supermarkets, its operational characteristics differ notably from regional supermarkets and community stores, potentially limiting the research results' applicability across different retail formats.

*2) Data Dimensionality Limitations:* Our research faces significant limitations in data foundation. While we obtained core operational data including sales transactions and inventory, improvements are needed in data dimensionality completeness and depth. Research findings indicate that the existing data structure primarily focuses on basic business aspects, failing to fully reflect retail business's full-chain characteristics.

The primary limitation manifests in the depth of consumer behavior data acquisition. Existing data fails to completely record members' entire purchase decision process, including product browsing trajectories, purchase intention conversion rates, and purchase time distributions. This lack of behavioral data significantly constrains the model's deep understanding and precise prediction of consumer purchasing patterns.

*3) Model Adaptability Limitations:* Despite the model's achievements in prediction accuracy and practical applications, several adaptability limitations persist. The model exhibits decreased prediction accuracy in scenarios lacking historical data support, such as new product launches. The response mechanism to market emergencies requires further refinement, particularly regarding prediction stability under irregular factors. Additionally, the model may face localization adaptation challenges in cross-regional applications, where regional consumption characteristic differences might affect prediction effectiveness.

### C. Future Research Prospects

*1) Data Integration and Extension:* To overcome single data source limitations, future research should focus on expanding data dimensions and sources. This expansion should proceed through several key initiatives:

First, establishing a multi-retail enterprise joint research framework to integrate sales data from various retail formats (large chain supermarkets, regional supermarkets, community convenience stores). This integration would enhance sample representativeness and universality.

Second, developing a multidimensional data collection system to deepen data acquisition and analysis regarding consumer behavior, market competitive environment, and supply chain collaboration. This development would provide more comprehensive input features for the prediction model.

*2) Model Optimization and Innovation:* To address existing prediction model adaptability issues, future research should concentrate on optimizing and innovating model architecture through several approaches:

First, exploring the integration of transfer learning mechanisms to enhance model performance in new product prediction and cross-regional application scenarios. Second, incorporating reinforcement learning technology to strengthen the model's response capability and adaptability to market emergencies. Third, researching deep learning models based on knowledge graphs to improve understanding and prediction capabilities for complex business environments.

*3) Application Scenario Expansion:* Future research needs to systematically explore the model's application potential across different retail scenarios through the following aspects:

First, conducting in-depth research on model adaptability across different product categories and regions, establishing scenario-based parameter tuning mechanisms. Second, exploring deep integration between prediction models and intelligent decision systems to achieve closed-loop optimization from prediction to decision-making. Finally, investigating prediction model application modes in new retail environments, particularly focusing on practical value in scenarios such as omnichannel sales and intelligent replenishment.

## VIII. Acknowledgments

We extend our gratitude to Supermarket X for providing valuable data support and implementation validation opportunities for this research.

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