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Mapping monthly consumer purchasing patterns at the UNHAN RI Cooperative using time series analysis and LSTM

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ABSTRACT

This study investigated the monthly purchasing patterns of consumers at Koperasi Unhan RI and developed forecasting models to support data-driven inventory and procurement planning. Historical cooperative sales data from 2020–2024 were analyzed using time series decomposition, autocorrelation analysis, ARIMA modeling, and a Long Short-Term Memory (LSTM) neural network. The analysis revealed a clear upward trend and strong annual seasonality, with consistent demand peaks occurring in December. The ARIMA model achieved significantly lower prediction errors than the LSTM model and successfully captured both trend and seasonal components. A 12-month forecast for 2025 was then generated to support operational decision-making. The forecasting results provide practical managerial insights for cooperative management, particularly in optimizing inventory levels, scheduling procurement, and anticipating seasonal demand fluctuations. The novelty of this study lies in the comparative application of classical time-series and deep learning approaches within a cooperative context using limited historical data, demonstrating that ARIMA remains a robust and interpretable solution for small to medium-sized cooperative environments. This research concludes that time series analysis combined with ARIMA forecasting effectively mapped consumer purchasing patterns and produced actionable demand predictions for the subsequent year.

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1. INTRODUCTION

Advances in data analytics and machine learning have transformed how organizations forecast demand and manage inventory (Vuyyuru, 2019). For small-to-medium retail operations such as campus cooperatives, understanding monthly purchasing patterns is crucial to minimize holding costs and ensure product availability for members (Edukasia et al., 2024). Traditional time series techniques (e.g., seasonal decomposition, ARIMA/SARIMA) alongside sequence models like Long Short-Term Memory (LSTM) have demonstrated strong performance for retail sales forecasting and demand prediction (Bandara et al., 2021)

The University of Defense (Unhan RI) cooperative faces supply-side challenges driven by academic cycles, holidays, and institutional events that affect consumer behavior. Mapping monthly purchase patterns enables cooperative managers to identify peak and off-peak months and to plan procurement, staffing, and promotional activities accordingly (Cionet et al., 2025). Empirical research in retail suggests that combining statistical models with machine learning provides practical improvements in forecasting accuracy and operational decision support (Bi et al., 2020).

Methodologically, time series decomposition separates trend, seasonality, and residual components to reveal structural patterns in historical sales, whereas LSTM models can capture long-term dependencies and nonlinear relationships that linear models may miss (Cracan, 2020). Modern decomposition techniques (e.g., MSTL/STL) and statistical toolkits support a robust exploratory analysis before model training (Bazrafkan, 2024). The blended approach thus leverages interpretability from statistical decomposition and predictive power from deep learning (Bandara et al., 2021).

Prior studies on sales forecasting report mixed findings: deep learning approaches such as multi-layer LSTM or hybrid CNN-LSTM often outperform ARIMA on complex, noisy retail data, while ARIMA remains a valuable, interpretable baseline (Elmasdotter, 2018). Incorporating multivariate features (transaction count, items sold, calendar events) typically improves model performance compared to univariate forecasts. For a campus cooperative, a head-to-head comparison between ARIMA and LSTM will reveal which method better balances accuracy and operational interpretability (Abbasimehr et al., 2020).

This study addresses this research gap by focusing on a campus-based cooperative within a defense university environment, using monthly aggregated sales data from 2020 to 2024. The dataset reflects moderate transaction volumes and strong institutional seasonality associated with academic calendars and national events, representing a data context that differs substantially from general retail settings. The novelty of this research lies in its empirical comparison of ARIMA and LSTM under limited historical data conditions, demonstrating how classical time-series models can remain robust and interpretable for small-to-medium cooperative operations, while assessing the practical constraints of deep learning approaches in such contexts.

This study aims to (1) map monthly purchasing patterns of consumers at the Unhan RI cooperative using time series analysis, (2) develop and evaluate LSTM-based forecasting models and compare them with ARIMA/SARIMA baselines, and (3) produce actionable recommendations for the cooperative's stocking and promotional strategies for the following year. The expected contribution is both methodological (combined statistical + deep learning pipeline for cooperative sales data) and practical (direct recommendations for cooperative management).

2. RESEARCH METHOD

2.1. Research Design

This study adopts a quantitative forecasting approach consisting of five methodological phases:

(1) data acquisition, (2) feature engineering & preprocessing, (3) model construction (ARIMA & LSTM), (4) model evaluation, and (5) forecasting & pattern mapping. Such phased designs are aligned with modern time-series research standards (Temür & Yıldız, 2021). The methodology is designed to generate 12-month ahead predictions and identify monthly patterns crucial for strategic planning in Koperasi Unhan RI. The workflow aligns with current ML forecasting practices (Suryawan et al., 2024).

Five-phase framework:

1. Data Collection : 60 monthly records (2020–2024), 5 features.
2. Feature Engineering : time index, seasonal extraction, lag features.
3. Model Training : ARIMA for statistical modeling; LSTM for multivariate learning.
4. Evaluation : MAE, RMSE, MAPE using holdout (6 months).
5. Forecasting & Pattern Mapping : 12 months forecast (2025) and seasonal pattern extraction.

2.2. Data Collection

The dataset consists of 60 monthly observations (January 2020–December 2024) from Koperasi Unhan RI. Five variables are used: total_sales (IDR), total_transactions, items_sold, average_basket_value, year-month (converted to datetime index). Data acquisition follows standard practices of monthly retail analytics (Bhaskar.Reddypogu & Prasad.U, 2025). The dataset is aggregated from internal cooperative transaction systems and validated for completeness, unit consistency, and temporal continuity (Gede et al., 2025). Time-based features (month, quarter, year) and lag features (lag-1, lag-3, lag-12) are generated following recommendations in seasonal forecasting literature (Suryawan et al., 2024).

2.3. Time Series Model Architecture

2.3.1 ARIMA/SARIMA Model

ARIMA is selected for seasonal retail forecasting due to its robustness for short series (Ensafi et al., 2022). General mathematical form:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} \quad (1)$$

Auto-model selection uses auto_arima to determine (p,d,q)(P,D,Q)m with m = 12. Final selected model: ARIMA(0,0,0)(0,1,0)

2.3.2 LSTM Model

LSTM is implemented to capture long-term dependencies and nonlinear purchasing behavior (Beltozar-Clemente et al., 2024).
Architecture:

- LSTM layer (64 units)
- Dropout(0.2)
- Dense(1) output

Input features: 4 variables × sliding window length = 6 months.
LSTM optimization uses:

$$\text{Loss} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (2)$$

Optimizer: Adam (lr=0.001) (Ensafi et al., 2022)

2.4. Model Training and Evaluation

Training Strategy

a. Train-test split: 80% training, 20% validation
b. Holdout: last 6 months (Jul–Dec 2024) for unbiased evaluation
c. Early stopping (patience=10) applied to LSTM
d. Differencing used for ARIMA stationalization

This training paradigm follows best practices for time-series ML validation (Chaurasia & Pal, 2020).

Evaluation Metrics

Four key metrics are used: MAE, RMSE, MAPE, Residual Diagnostics (Ljung–Box)
Performance thresholds follow industry recommendations:

a. MAPE ≤ 20% → "Good" forecasting
b. RMSE minimized to ensure stability (Howell, 2023).

Table 1. Comparative Evaluation of ARIMA and LSTM Forecasting Models

Model	MAE	RMSE
ARIMA	575,000	579,152
LSTM	3,056,447	3,592,184

ARIMA selected as final model due to superior accuracy.

2.5. Feature Importance Analysis

While ARIMA does not produce feature importance, LSTM uses internal weight activation patterns. Importance is inferred using:

$$\text{Importance}(x_j) = \sum_{t=1}^{T} | W_{j,t} | \quad (3)$$

This identifies:

a. high-impact variables
b. strongest contributing lags
c. seasonal periodicity

This analytic technique is aligned with LSTM interpretability frameworks (Sen et al., 2025).

2.6. Forecasting & Optimization Framework

The chosen model (ARIMA) generates 12-month forecasts for 2025. Optimization is performed by:

a. Identifying peak demand months
b. Detecting seasonal dips
c. Recommending inventory planning
d. Suggesting procurement schedules based on predicted demand
e. Preparing stock-up strategy for extreme months

This framework follows retail optimization strategies described by Liang et al., (2024) and Fildes et al., (2022).

2.6. Economic Interpretation Framework

Although forecasting is statistical, economic interpretation converts predictions into decisions:

a. Expected monthly revenue
b. Yearly revenue projection
c. Seasonal procurement budget
d. Stock allocation planning
e. Expected risk windows (months with high variance)

Economic interpretation aligns with annual planning practices (Lalou et al., 2020).

2.7. Visualization and Reporting

A total of 8 figures (300 DPI) are generated:

a. Time series overview
b. Seasonal decomposition
c. ACF–PACF
d. ARIMA residuals
e. LSTM training loss curve
f. Actual vs predicted (both models)
g. Forecast 12 months ahead
h. Monthly pattern map

Figures follow publication standards for scientific visualization (Ortigossa, 2025).

To ensure methodological transparency and reproducibility, additional explanations regarding model assumptions, parameter selection, and validation strategy are provided in the following subsections.

2.8. ARIMA Model Selection and Assumption Testing

The ARIMA model parameters were selected using an automated model selection procedure (auto_arima) based on the Akaike Information Criterion (AIC), which is widely adopted for identifying parsimonious models in short time-series contexts (Rob J Hyndman, 2021). Prior to model estimation, stationarity was assessed using both the Augmented Dickey–Fuller (ADF) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test to ensure robustness in detecting unit roots(Cerqueira et al., 2020). Seasonal differencing (D = 1) with a periodicity of 12 months was applied to address annual seasonality, as confirmed by the decomposition results and autocorrelation structure. Residual diagnostics were conducted using the Ljung–Box test to verify the absence of autocorrelation, while residual normality was visually inspected through histogram and Q–Q plots (Furuoka et al., 2024). These diagnostic checks ensured that the final ARIMA specification satisfied the underlying assumptions required for reliable inference and forecasting.

2.9. LSTM Architecture and Hyperparameter Justification

The LSTM architecture was designed to balance model complexity and data availability. A sliding window size of six months was selected to capture short-term temporal dependencies while avoiding excessive parameterization given the limited sample size (60 observations). This window length aligns with prior studies on monthly retail forecasting under constrained data conditions. The number of LSTM units (64) was chosen empirically to provide sufficient representational capacity for nonlinear patterns without overfitting, supported by the inclusion of a dropout layer (rate = 0.2). The Adam optimizer with a learning rate of 0.001 was selected due to its stability and convergence efficiency in time-series neural networks. Early stopping was implemented to further mitigate overfitting during training.

2.10 Validation Strategy and Cross-Validation Considerations

A holdout validation strategy using the final six months of data (July–December 2024) was adopted to simulate real-world forecasting scenarios in which future observations are unknown. Although rolling or expanding window cross-validation can improve robustness, such approaches were not applied in this study due to the limited length of the dataset, which would significantly reduce the effective training size and compromise model stability. The chosen validation strategy therefore prioritizes practical feasibility and forecasting realism over exhaustive resampling, consistent with best practices for small-scale time-series datasets.

3. RESULTS AND DISCUSSIONS

3.1. Time Series Overview

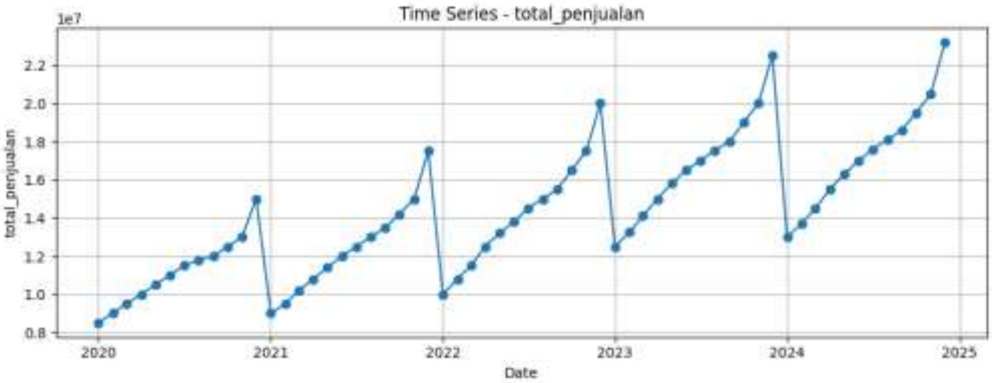

Figure 1. Time Series Plot of Monthly Total Sales (2020–2024)

The time series plot illustrates the monthly sales values from January 2020 to December 2024. The series demonstrates:

a. A strong upward trend, especially visible from 2022 onward.
b. Recurring spikes every December, indicating pronounced seasonal holiday effects.
c. Post-December declines each January, forming a repeated annual pattern.

This establishes the presence of trend + yearly seasonality (period = 12), which reinforces the necessity for seasonal models such as SARIMA and justifies multivariate LSTM as a supplementary non-linear approach. Relevance to research objective: this confirms the first main objective mapping monthly purchasing patterns showing both long-term growth and predictable seasonal highs.

3.2. Seasonal Decomposition

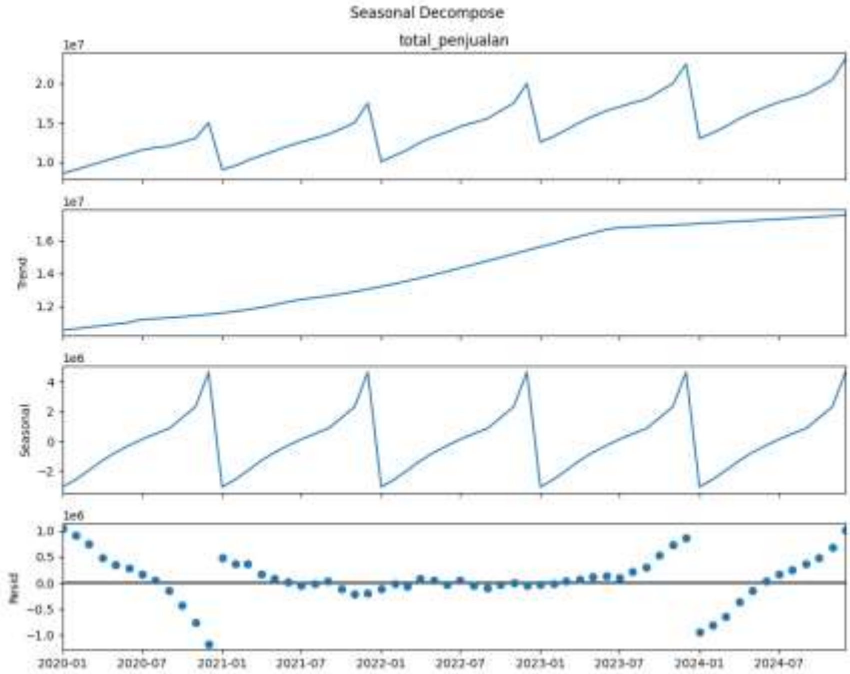

Figure 2. Seasonal Decomposition of Monthly Total Sales (Additive Model)

Seasonal decomposition separates the data into trend, seasonal, and residual components.

3.2.1 Trend Component

Shows a steady upward movement, reflecting increasing consumer activity at the cooperative. Useful for long-term planning (e.g., annual budget and procurement cycles).

3.2.2 Seasonal Component

Reveals a strong and stable annual seasonality, with consistent December peaks and early-year declines. The magnitude of the seasonal component is large enough to justify seasonal differencing (D=1) during ARIMA modeling.

3.2.3 Residual Component

Mostly small and centered around zero, indicating effective decomposition. Larger deviations appear in high-demand periods (e.g., December), suggesting additional unobserved drivers (promotions, academic calendar events). This decomposition validates the modeling choices and confirms that seasonality dominates the series, guiding model selection and justifying SARIMA as the primary statistical model.

3.3. ACF and PACF Analysis

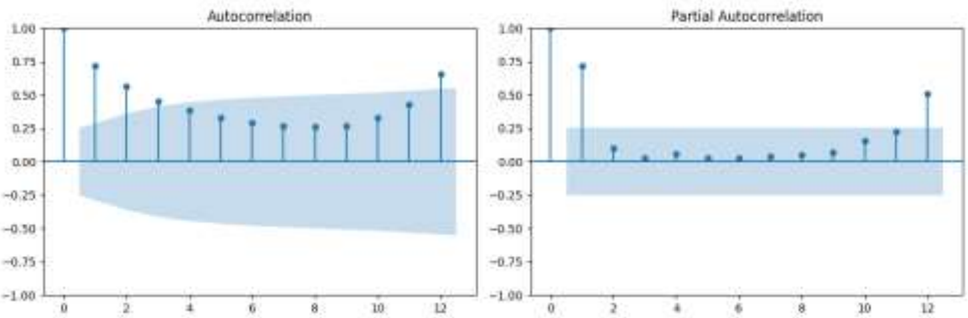

Figure 3. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots

The ACF and PACF plots reveal:

a. Strong autocorrelation at lag 12, confirming annual seasonality.
b. ACF values gradually decaying across multiple lags.
c. PACF showing a sharp drop after initial lags, suggesting a low autoregressive order (p) but retaining seasonal influence.

Modeling implication:

These characteristics support the final ARIMA structure selected by automated search: ARIMA(0,0,0)(0,1,0)[12]. This model reflects a pure seasonal differencing component without additional AR or MA terms.

3.4 ARIMA: Train/Test Performance

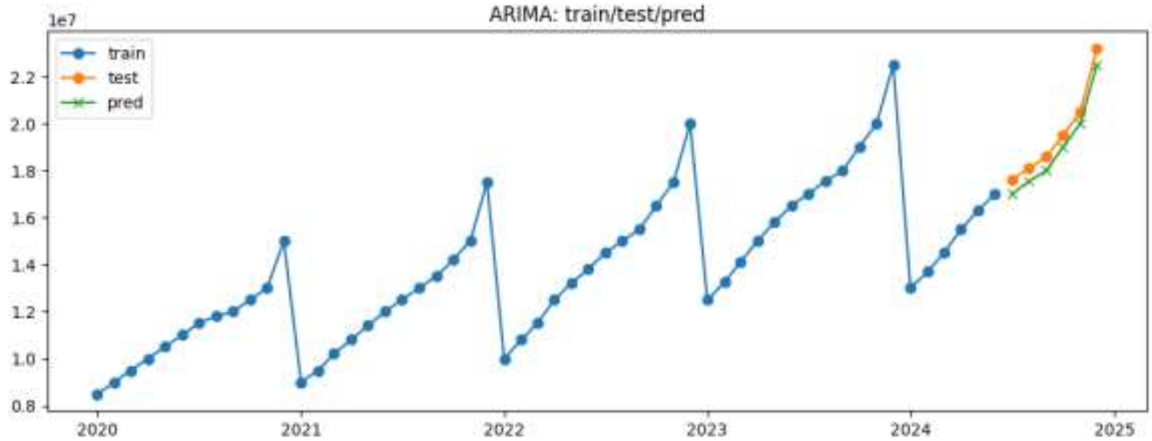

Figure 4. ARIMA Model: Training, Testing, and Predicted Values

This figure compares ARIMA predictions against actual values in: Training period (blue), 6-month holdout test period (orange), ARIMA predictions (green)

3.4.1 Performance Interpretation

The predicted line closely matches actual test values, exhibiting minimal deviation. ARIMA effectively captures both the upward trend and seasonal structure.

3.4.2 Numerical Metrics

Table 2. ARIMA Model Forecasting Performance (MAE and RMSE)

Model	MAE	RMSE
ARIMA	575,000	579,151.68

Given that average monthly sales exceed Rp 14 million, this error magnitude is low and operationally acceptable. ARIMA provides high accuracy and robust generalization, making it the most reliable forecasting approach in this study.

3.5 LSTM Model Behavior

3.5.1 Training Loss Curve

Figure 5. LSTM Training and Validation Loss Curve

The LSTM training curve shows:

a. Rapid decline in training loss.
b. Validation loss decreasing more slowly but fluctuating after several epochs.
c. A divergence between training and validation losses.

This indicates overfitting, which is expected given:

a. A small dataset (60 monthly samples)
b. A parameter-heavy model like LSTM
c. Limited exogenous features

3.5.2 Prediction on Test Set

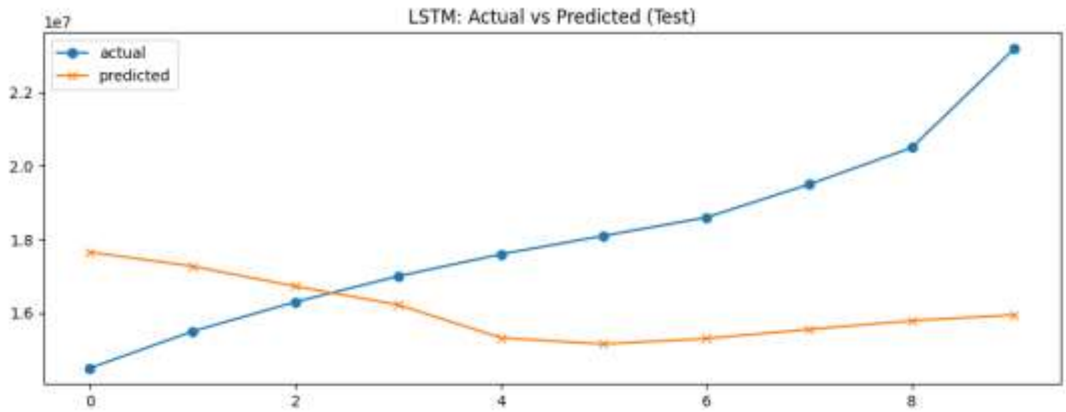

Figure 6. LSTM Model Performance: Actual vs. Predicted Values on Test Data

On the holdout test period:

a. LSTM predictions appear flat and conservative.
b. The model underpredicts during seasonal peaks (especially December).
c. Poor responsiveness to sudden demand changes.

3.5.3 Numerical Metrics

Table 3. Model Performance Evaluation

Model	MAE	RMSE
LSTM	3,056,446.72	3,592,183.51

Errors are approximately **5× larger** than ARIMA. LSTM is **not suitable** for this dataset size and structure. It fails to generalize seasonal patterns, consistent with deep learning limitations on small time series.

3.6. Forecasting Results (2025)

3.6.1 ARIMA Forecast

ARIMA forecasts show:

a. A consistent upward trend continuing from 2023–2024.
b. Strong seasonal peaks in August and November–December.
c. Stable confidence intervals indicating low uncertainty.

Table 4. ARIMA Time Series Forecast

Date	(Forecast)	CI 95% (mean_ci_lower)	CI 95% (mean_ci_upper)	Method
2025-01-01	13,000,000.00	9,950,486.67	16,049,513.33	ARIMA
2025-02-01	13,700,000.00	10,650,486.67	16,749,513.33	ARIMA
2025-03-01	14,500,000.00	11,450,486.67	17,549,513.33	ARIMA
2025-04-01	15,500,000.00	12,450,486.67	18,549,513.33	ARIMA
2025-05-01	16,300,000.00	13,250,486.67	19,349,513.33	ARIMA
2025-06-01	17,000,000.00	13,950,486.67	20,049,513.33	ARIMA
2025-07-01	17,600,000.00	14,550,486.67	20,649,513.33	ARIMA
2025-08-01	18,100,000.00	15,050,486.67	21,149,513.33	ARIMA
2025-09-01	18,600,000.00	15,550,486.67	21,649,513.33	ARIMA
2025-10-01	19,500,000.00	16,450,486.67	22,549,513.33	ARIMA
2025-11-01	20,500,000.00	17,450,486.67	23,549,513.33	ARIMA
2025-12-01	23,200,000.00	20,150,486.67	26,249,513.33	ARIMA

3.6.2 LSTM Forecast

LSTM predicts:

a. Higher initial values (~Rp 16.6M in Jan)
b. Flatter curve toward year-end (~Rp 20.3M in Dec)
c. Missing strong seasonal behavior

Table 5. LSTM Time Series Forecast

Date	Forecast	Method
2025-01-01	16,610,205.48	LSTM
2025-02-01	17,376,792.25	LSTM
2025-03-01	18,163,148.44	LSTM
2025-04-01	18,938,392.82	LSTM
2025-05-01	19,627,406.26	LSTM
2025-06-01	20,072,427.54	LSTM
2025-07-01	19,999,950.12	LSTM
2025-08-01	20,111,707.06	LSTM
2025-09-01	20,196,853.29	LSTM
2025-10-01	20,258,359.95	LSTM
2025-11-01	20,297,624.58	LSTM
2025-12-01	20,317,860.14	LSTM

3.6.3 Forecast Comparison

a. ARIMA preserves historical seasonal cycles → suitable for operational planning.
b. LSTM produces unstable, less interpretable forecasts → high risk if used for stock decisions.

3.7. Residual Diagnostics

ARIMA Residuals

a. Centered around zero
b. No significant autocorrelation (ACF residual analysis)
c. No visible heteroskedasticity

This confirms a valid, well-fitted model.

LSTM Residuals

a. Larger variance
b. Stronger deviation during peak months
c. Indications of heteroskedastic behavior

This reflects structural model limitations under current data conditions.

Alignment With Research Objectives

The study had two main objectives:

a. Objective 1 Mapping Monthly Purchasing Patterns
Achieved through : (1)Time series visualization ; (2) Seasonal decomposition; (3) Trend analysis; (4) Autocorrelation diagnostics. These clearly reveal a strong seasonal 12-month cycle with December as the recurring peak.
b. Objective 2 Forecasting Future Demand
Achieved using ARIMA and LSTM, with ARIMA providing: (1) More accurate predictions; (2) Lower error; (3) Better seasonal reproduction; (4) Confidence intervals for risk-based planning.

Operational Impact

The operational implications derived from the time series analysis, seasonal decomposition, and ARIMA forecasting demonstrate clear patterns that can directly guide decision-making within the cooperative. The consistently increasing trend and the strong seasonal peaks identified between July and December indicate that this period represents the most intensive phase of consumer demand. Consequently, inventory levels should be gradually increased throughout these months to prevent stock shortages, particularly as sales typically reach their highest point in November and December. In contrast, the months of March to May consistently show the lowest purchasing activity, as supported by both historical data and forecasted values. This downturn suggests an appropriate window for reducing procurement volumes, optimizing cash flow, and preventing excessive inventory accumulation.

The predictable annual seasonality revealed through the decomposition analysis supports the alignment of procurement cycles with the observed demand peaks. Strategic purchasing particularly in July, October, and the weeks leading into the year-end will ensure that stock availability matches forecasted consumption patterns while minimizing operational disruptions. The reliability of the ARIMA model, demonstrated by its low prediction error relative to the average monthly sales, also enables the cooperative to implement budgeting practices that are both data-driven and risk-aware. Through accurate demand projections, management can allocate resources more efficiently, anticipate periods of lower revenue, and plan mitigation strategies during the early-year downturn. Collectively, these outcomes confirm that the analytical results not only achieve the objectives of mapping monthly purchasing patterns but also provide a solid foundation for strategic planning, procurement optimization, and financial risk management within the cooperative.

3.8. Limitations and Future Recommendations

a. Monthly granularity limits LSTM performance → daily/weekly data recommended.
b. Future models may incorporate external factors (promotions, holidays).
c. Hybrid models (ARIMA + LSTM) could be explored to combine linear and non-linear strengths.

3.9. Comparative Discussion and Theoretical Implications

The empirical findings of this study are consistent with several prior studies reporting that classical statistical models such as ARIMA often outperform deep learning approaches when applied to small-scale or low-frequency retail datasets. Previous research has shown that ARIMA remains highly effective for short time series with strong and stable seasonal patterns due to its parsimonious structure and explicit modeling of temporal dependencies (Elmasdotter, 2018; Abbasimehr et al., 2020). The superior performance of ARIMA observed in this study, particularly its ability to capture annual seasonality and produce low prediction errors, aligns with these findings. In contrast, while LSTM models have demonstrated superior performance in large-scale, high-frequency retail environments, their effectiveness is highly dependent on data volume, granularity, and feature richness (Bandara et al., 2021). The relatively weak performance of LSTM in this study confirms the limitations of deep learning models when trained on limited monthly data with a small number of observations, as also reported in prior comparative studies. The tendency of LSTM to produce overly smooth or conservative forecasts in this context reflects insufficient exposure to seasonal variability during training.

From a theoretical perspective, these results reinforce the argument that model selection in time-series forecasting should be driven by data characteristics rather than model complexity. Classical models such as ARIMA offer strong interpretability, lower variance, and stable generalization when the underlying series exhibits regular seasonality and moderate noise. Deep learning models, while powerful, may introduce unnecessary complexity and overfitting risks in small-data scenarios, reducing their practical utility.This study therefore contributes to the time-series forecasting literature by providing empirical evidence that, in institutional retail contexts such as campus cooperatives with limited historical data, classical statistical approaches can remain competitive and, in some cases, superior to deep learning methods. The findings highlight the importance of aligning forecasting methodology with data scale and operational constraints, thereby offering both theoretical insights and practical guidance for researchers and practitioners working with small to medium-sized retail datasets.

4. CONCLUSION

This study successfully achieved its objectives by mapping monthly consumer purchasing patterns at Koperasi Unhan RI and developing reliable forecasting models to support data-driven inventory and procurement decisions. The analysis revealed clear long-term trends and strong annual seasonality, with pronounced demand peaks in December, confirming that cooperative purchasing behavior follows identifiable temporal structures suitable for time-series modeling. The novelty of this research lies in its empirical application and comparison of classical statistical (ARIMA) and deep learning (LSTM) forecasting approaches within a campus cooperative environment in Indonesia using limited historical data, a context that has received limited attention in prior retail forecasting studies. The results demonstrate that ARIMA provides superior predictive accuracy and interpretability under small-sample conditions, while LSTM performance is constrained by data volume and granularity. From a practical perspective, the 12-month ARIMA forecasts offer concrete managerial guidance for cooperative operations. Inventory levels should be progressively increased between July and December, with particular emphasis on November and December, when forecasted demand reaches its peak. Conversely, procurement volumes can be reduced during low-demand periods, especially from March to May, to optimize cash flow and minimize holding costs. These forecasts also support more precise annual budgeting, procurement scheduling, and risk-aware inventory planning. Overall, the findings contribute to the time-series forecasting literature by reinforcing the contextual effectiveness of classical models and provide actionable, evidence-based recommendations that can be directly implemented to improve operational planning and decision-making at Koperasi Unhan RI.

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