



## RESEARCH ARTICLE

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# MULTI-SKU RETAIL SALES FORECASTING WITH FP-GROWTH ASSOCIATION-RULE FEATURES: A COMPARATIVE STUDY OF ECHO STATE NETWORK AND LSTM

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## ABSTRACT

This study examines whether cross-product signals derived from market-basket transactions can enhance multi-SKU retail sales forecasting when embedded as auxiliary features in global sequence models. Retail transaction records from January 2024 to November 2025 were utilized. Frequent itemsets and association rules were mined using FP-Growth, and the resulting co-purchase structure was transformed into forecasting features. Daily sales were aggregated into weekly multivariate series and normalized using Min–Max scaling. Two feature-augmented forecasting architectures were evaluated: an Echo State Network (ESN+FP) and a Long Short-Term Memory network (LSTM+FP). Hyperparameters were tuned with Optuna (30 trials) using validation sMAPE, and per-SKU performance was assessed using MAE and sMAPE. Across 43 Food & Beverage SKUs, the lowest sMAPE was obtained by ESN+FP for 28 SKUs, whereas LSTM+FP performed best for 15 SKUs, indicating substantial heterogeneity in demand dynamics. Although slightly lower average errors were achieved by LSTM+FP, ESN+FP yielded superior results for several volatile yet repetitive series, while more stable trend patterns were better captured by LSTM+FP. An adaptive, per-SKU model selection strategy is therefore supported.



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## I. INTRODUCTION

Digital transformation in the retail sector has intensified the need for accurate demand forecasting and inventory control. In highly competitive markets with large product portfolios and rapidly evolving consumer behavior, forecasting errors directly increase holding costs, raise stockout risk, and reduce revenue. These challenges are amplified in multi-SKU settings because operational decisions are often made at the item level while demand across products can be interdependent. Transaction data frequently exhibit complementary and substitution relationships, making cross-product signals valuable for more stable and generalizable forecasts. A wide range of demand-forecasting methods has been applied in retail and supply chains, from statistical baselines to regression-based machine-learning models, largely due to their operational simplicity and competitive short-horizon performance. Comparative studies on industrial demand forecasting also show that the choice of algorithm and modeling strategy (e.g., global vs. local) affects the accuracy and consistency of cross-item/series performance [1], while comparative studies in the context of data-driven logistics confirm the common practice of comparing statistical methods with ML for time series [2]. In recent years, deep learning (e.g., LSTM/RNN variants) has been increasingly adopted to capture nonlinear dynamics in demand forecasting, including in e-retail and industry/food data-based demand forecasting [3], [4], [5].

However, in practice, many approaches still emphasize item-specific temporal pattern learning or rely on implicit cross-series learning (e.g., through global/local strategies or multivariate modeling), without explicit and measurable mechanisms to represent co-purchase/shopping basket structures. This challenge is compounded by heterogeneous SKU-level dynamics and disruptions such as outliers and calendar effects, which can destabilize model selection and generalization [1], [6]. Additionally, the intermittent demand characteristics of some retail products have been explicitly reported and require special attention in feature design, modeling strategies, and evaluation [7]. Association-rule mining provides an explicit mechanism for extracting cross-product signals from transaction data. Algorithms such as Apriori and FP-Growth have been widely used to extract frequent itemsets and association rules that represent co-purchase tendencies, and support cross-selling analysis and bundling promotion design [8]. However, the use of association analysis outputs as predictive features in time series forecasting is still relatively limited; many studies stop at descriptive findings (co-purchase patterns) without systematically integrating them into quantitative forecasting frameworks trained and evaluated at the SKU level. This limitation leaves clear room for research: can the co-purchase structures mined from transactions be transformed into features that enrich multi-SKU forecasting models and provide consistent improvements for specific SKUs, especially for volatile or infrequent series? Beyond LSTM as a widely used sequence-learning approach, Echo State Networks (ESN) offer a computationally efficient RNN alternative.

Unlike LSTM, which trains network weights end-to-end, ESN uses a reservoir with fixed weights and only optimizes output weights, making its training relatively lightweight and practical when applied to multi-SKU scenarios that require model/configuration maintenance across multiple outputs [9]. Comparative studies on dynamic systems also show that reservoir computing can be a competitive alternative to LSTMs for certain prediction tasks, while providing perspective on the accuracy–efficiency trade-off between fully-trained and reservoir-based approaches [10]. These characteristics are relevant to retail needs: useful prediction solutions must be accurate, but also feasible to run efficiently on large data and periodic model updates. Based on this gap, this study proposes a multi-SKU retail sales forecasting framework that integrates FP-Growth-based cross-product features with two different sequence forecasting architectures, namely ESN and LSTM. FP-Growth is used to extract inter-product correlation patterns from transactions and distill them into features/feature selections that represent co-purchase structures, so that the model learns not only from the historical temporal patterns of each SKU, but also from the cross-SKU relationships that emerge in shopping baskets. Furthermore, this study evaluates two global model variants—LSTM+FP and ESN+FP—on a like-for-like basis with consistent tuning procedures and per-SKU evaluation using MAE and sMAPE on weekly time series. Using transaction data from January 2024 to November 2025 filtered to the Food & Beverage category, the experiments focused on 43 SKUs that met the weekly history eligibility criteria.

## II. RELATED WORK

Multi-item retail forecasting studies commonly retain classical baselines (e.g., ARIMA, exponential smoothing) and regression-style ML models due to their training efficiency, competitive short-horizon accuracy, and ease of deployment. In the context of grocery retail, Liashenko and Yakymchuk emphasize model selection as a practical decision under exogenous shocks (e.g., pandemics) and interpretability requirements; they discuss comparisons of classical time series methods with ML regression and additive approaches that support covariates (e.g., the Prophet family) to capture trends, seasonality, holidays, and external variables [11]. This direction is consistent with the literature's practice of demanding a robust and easily explainable baseline before proposing more complex architectures, especially when the study's goal is not just accuracy but also applicability and transparency of assumptions [11]. As data complexity increases and the need to capture non-linearities grows, the demand/time-series forecasting literature increasingly highlights deep learning designs that combine temporal memory (LSTM/GRU) with feature extractors (CNN/TCN) or attention mechanisms to model both local patterns and longer dependencies. In retail sales, Moraes et al. proposed a hybrid CNN–LSTM variant (stacked and parallel) that uses LSTM for temporal dynamics and convolutional modules to extract multivariate/exogenous information, and they reported improved performance over simpler neural architectures and autoregressive baselines on multivariate retail data [12]. In other time series domains, similar hybrid designs are widely used to combine linear/non-linear structures and balance feature representation needs against training load; for example, Nandigam et al. explore CNN–LSTM for large-scale energy consumption forecasting as an example where complex patterns and covariates drive the use of hybrid models [13]. Conceptually, these results reinforce the argument that "sequence memory + feature extraction" becomes the dominant design pattern when series are multivariate, influenced by external factors, and have variable structures.

Beyond hybrid CNN–RNN, two other relevant lines of research are (i) modeling multivariate dependencies and long contexts through attention/Transformer and (ii) improving robust forecasting for long horizons. Cheng et al. introduced SeriesNet as a conditional forecasting architecture that combines a causal CNN component with an RNN and then adds attention to improve temporal feature learning without uncontrolled parameter growth [14]. For contexts demanding long dependencies and complex covariates, the Transformer approach—e.g., Temporal Fusion Transformer (TFT)—is also frequently chosen; Alorf and Khan position TFT as a framework for capturing long-term dependencies in complex meteorological time series (with decomposition) [15]. On the robust long-horizon forecasting side, Zhou et al. propose TreeDRNet (based on arXiv) as an example of a deep approach targeting robustness in long-term predictions [16]. Furthermore, cross-dataset comparative studies are also commonly conducted to avoid single claims based on one dataset; Altıparmak and Aksu exemplify the practice of comparing several deep learning approaches for installed capacity forecasting, showing that "state-of-the-art" assessments often depend on evaluation protocols and data characteristics [17]. Overall, the deep forecasting literature tends to move in two directions: enriching mechanisms for capturing cross-variable dependencies (attention/Transformer) and strengthening robust generalization for long horizons, while still demanding rigorous comparison and replication on diverse datasets [14], [15], [16], [17]. However, in the representative works above, cross-product dependencies in retail are generally handled implicitly through multivariate inputs, convolutional modules, or attention—not through signals derived directly from the "market-basket" transaction structure. In fact, classical association-rule mining is designed to extract cross-item co-purchase patterns from large-scale transaction data, with Apriori as the initial foundation of association rules [18] and FP-Growth as an efficient method without candidate generation for frequent pattern mining [19].

The absence of an explicit path from "basket → rules → predictive features" in retail deep forecasting studies (e.g., retail CNN–LSTM [12]) leaves clear room for feature engineering that injects co-purchase structures as more interpretable cross-SKU signals, especially when the target is global multi-SKU forecasting and per-SKU evaluation. On the alternative architecture side, reservoir computing such as Echo State Networks (ESN) is often considered for its training efficiency (only readouts are trained, reservoir remains fixed), making it attractive for multiple series/tuning experiment scenarios. The foundational ESN literature emphasizes the importance of the "echo state property" condition and performance sensitivity to reservoir design/dynamics [20], [21], [22]. However, neat and direct comparative evidence for ESN vs. LSTM in the context of multi-SKU retail—with aligned features and per-SKU evaluation—is still much less common than comparisons between deep network variants (e.g., CNN–LSTM vs. other approaches) or cross-architecture benchmark studies [12], [17]. Therefore, this study is positioned as a focused empirical contribution: testing ESN and LSTM as global models with aligned FP-Growth features, then interpreting their trade-offs based on per-SKU performance.

### III. MATERIALS AND METHODS

#### III.1 DATA

The data used in this study were obtained from retail sales transactions at Retail Ayu Nadi covering January 2024 to November 2025. The initial dataset consists of 2,097,150 rows and 27 attributes representing transaction information at the receipt level, including transaction time, invoice number, product identity, quantity, and other sales-related attributes. In the initial stage, attributes that were originally only recognized by column index were relabeled. The five key attributes used were date\_time (transaction timestamp), invoice\_number, item\_name, quantity, and item\_category. Transaction data from 2024 and 2025 were combined into a single integrated data frame. Furthermore, the scope of the study was limited to the Food & Beverage category to maintain relevance to daily consumer goods; other categories were excluded. After this filtering process, the number of transactions was reduced to 1,026,524 rows. From all Food & Beverage products, a set of items that appeared in the FP-Growth association rule results and also had a long weekly sales history was selected. This process resulted in 43 SKUs that became the focus of multi-SKU modeling at the forecasting stage.

#### III.2 DATA PREPROCESSING

Preprocessing followed two parallel pipelines: association extraction and time-series construction, which subsequently served as inputs to ESN+FP and LSTM+FP. The complete diagram of the FP-Growth flow integrated with ESN and LSTM modeling is shown in Figure 1 and Figure 2. For association extraction, transactions were converted into shopping baskets using the invoice identifier (no\_nota). The FP-Growth algorithm is used to perform frequent itemset mining with a certain minimum support threshold. This method extracts combinations of products that frequently appear together in a transaction. Association rules were derived from frequent itemsets, with confidence computed as shown in following equation [23]:

$$\text{Support}(X) = \frac{\text{Transactions Contains With } X}{\text{Total Transactions}}$$

$$\text{Confidence}(A \rightarrow B) = \frac{\text{Support}(A \cup B)}{\text{Support}(A)}$$

The resulting rules were evaluated using lift, and only rules with lift > 1 and support/confidence above the specified thresholds were retained to preserve statistically meaningful relationships [24]. The items involved in the selected association rules are reintegrated into the transaction dataset. Only transactions containing these products are used in modeling, so that the model focuses on products that have clear transactional relevance. This step also functions as association-based feature selection and reduces noise from irrelevant items [25]. For time-series construction, daily transactions were aggregated into weekly series by summing item-level sales over Monday–Sunday intervals. Weekly aggregation is chosen to reduce daily stochastic fluctuations and sparsity issues (many zero values) that are common in daily retail data, while maintaining trend and seasonal patterns that are relevant for decision making [26]. The aggregation results are then pivoted to obtain a multivariate time series matrix, with rows representing weeks and columns representing items. Missing values that arise due to pivoting are filled with zeros. Finally, all weekly sales values are normalized using Min–Max scaling to the range [0, 1]. This normalization is important to stabilize the learning process in both the ESN reservoir and the LSTM network, which are sensitive to differences in scale between variables. This scaled multivariate time series matrix becomes the database for the multi-SKU experiment in the next stage.

#### III.3 ESN+FP MODEL ARCHITECTURE AND TRAINING

The Echo State Network architecture with FP-Growth association features (ESN+FP) is designed as a global multi-SKU model that utilizes dynamic reservoir representations to predict weekly sales. The complete flow of FP-Growth and ESN integration is shown in Figure 1.

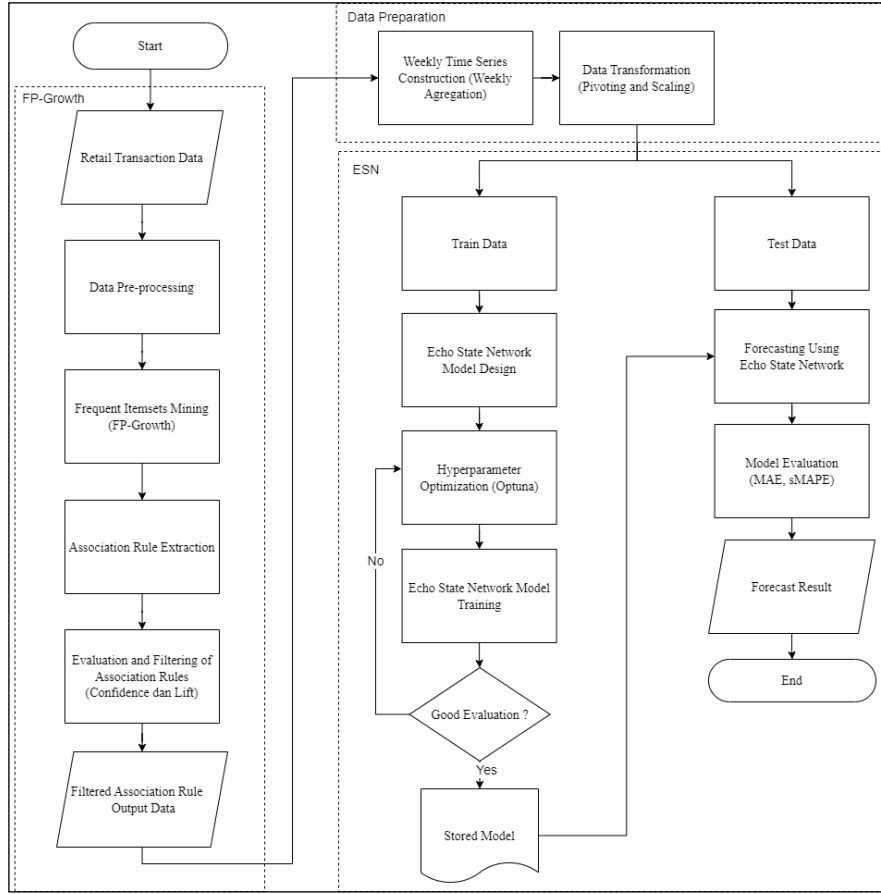


Figure 1: ESN+FP workflow for multi-SKU weekly sales forecasting.  
Source: Authors, (2026).

Structurally, ESN consists of three main components: an input layer, a reservoir with random recursive weights, and an output layer (readout) [27]. The input and reservoir weights ( $W_{in}$  and  $W$ ) are randomly initialized with controlled sparsity and spectral radius to satisfy the Echo State Property, thereby keeping the reservoir dynamics stable [28]. At each weekly time step, the input vector contains scaled sales for all relevant SKUs along with additional features from FP-Growth (e.g., membership indicators or association intensity). The reservoir projects this input into a high-dimensional, nonlinear state space. Unlike conventional RNNs, the ESN training phase only optimizes the output weights  $W_{out}$ , while  $W_{in}$  and  $W$  remain fixed. The training process begins with state harvesting, which involves feeding the training time series into the reservoir and recording the internal state matrix  $H$  [29] [30]. The first few steps are ignored as a washout period to eliminate the effects of initial conditions. The output weights are then calculated using ridge regression.

$$W_{out} = Y_{target} H^T (H H^T + \lambda I)^{-1}$$

where  $Y_{target}$  is the sales target matrix,  $\lambda$  is the regularization coefficient, and  $I$  is the identity matrix. Because ESN performance is sensitive to reservoir configuration, Optuna was used for hyperparameter optimization using the TPE sampler over reservoir size, spectral radius, leak rate, and ridge coefficient. This process utilizes the Tree-structured Parzen Estimator (TPE) algorithm to explore combinations of parameters such as reservoir size, spectral radius, leak rate, and regularization coefficient [31]. A total of 30 trials were run to minimize the sMAPE value on the validation data. The best hyperparameters were then used to train the final ESN+FP model on the training data. All model components, including the scaler and pivot structure, were stored in a serialized format to ensure consistency when performing inference on new data.

#### III.4 LSTM+FP MODEL ARCHITECTURE AND TRAINING

The second model is Long Short-Term Memory with FP-Growth association features (LSTM+FP), which is also configured as a global multi-SKU model. The integration flow diagram of FP-Growth and LSTM is shown in Figure 2.

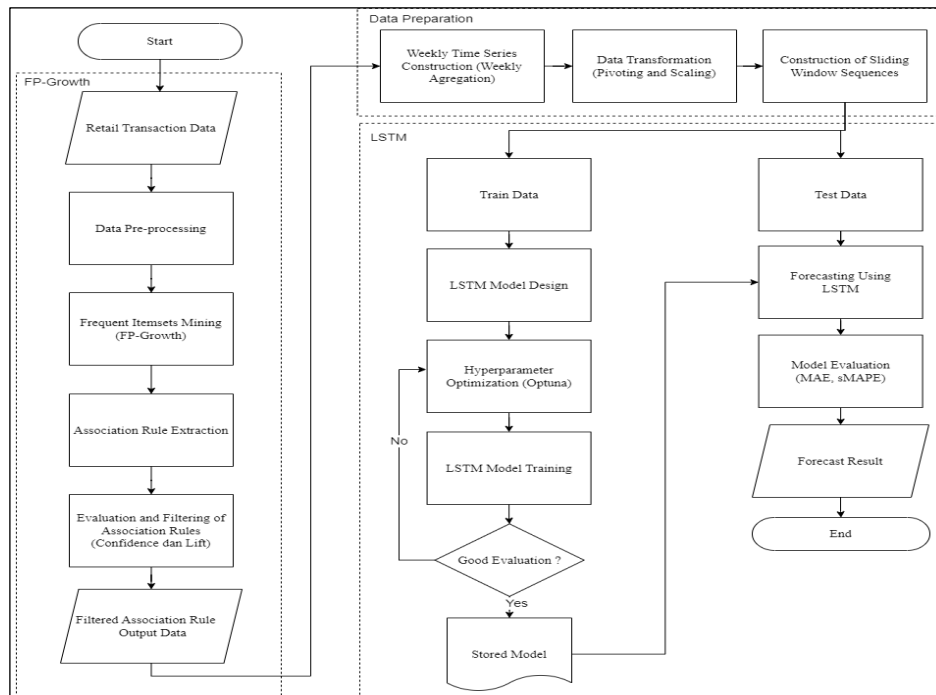


Figure 2: LSTM+FP workflow for multi-SKU weekly sales forecasting.  
Source: Authors, (2026).

In contrast to ESN, LSTM employs gated memory cells (input, forget, and output gates) to learn long-range temporal dependencies. After the weekly aggregation and normalization stages, the multivariate time series matrix is converted into a fixed sequence using the sliding window approach[32]. Each window contains historical observations spanning  $L$  weeks for all SKUs, while the target is the next week's sales vector. This transformation allows LSTM to learn temporal patterns across multiple time steps[32]. The network architecture consists of one or more LSTM layers followed by a fully connected layer that produces multivariate predictions. All network weights are trained through backpropagation through time[33]. As in ESN, the LSTM configuration is tuned using Optuna with 30 trials to minimize sMAPE on the validation data. The optimized hyperparameters include the number of LSTM units, sequence length, learning rate, batch size, number of epochs, and dropout rate[33]. The training process was carried out with the Adam optimizer and an error-based loss function (e.g., MSE), with several epochs until convergence. The model that performed best on the validation data was selected as the final model. As with ESN+FP, the LSTM+FP model along with the pre-processing components (scaler, pivot structure, and window configuration) were saved for use in the forecasting and evaluation stages.

### III.5 EXPERIMENTAL DESIGN AND EVALUATION

The experiment was designed to compare the capabilities of ESN+FP and LSTM+FP in the context of multi-SKU sales forecasting. Given the sequential nature of time series, the training and test data were separated chronologically. Several train–test ratio scenarios (60:40, 70:30, and 80:20) were evaluated to test the robustness of the model against variations in training data length, with the final model selected based on the best performance in the scenario considered most representative. In each scenario, both models were trained as global models using the same multivariate time series matrix, which had been enriched with FP-Growth association features. The evaluation was performed per SKU, so that for each item a pair of error values was obtained for ESN+FP and LSTM+FP. Two main metrics were used, namely Mean Absolute Error (MAE) and Symmetric Mean Absolute Percentage Error (sMAPE). MAE measures the average absolute deviation between actual and predicted values, while sMAPE provides a measure of relative error normalized to the average of actual and predicted values, making it easier to compare SKUs with different sales scales.

## IV. RESULT AND DISCUSSION

### IV.1 COMPARATIVE PERFORMANCE RESULTS

In this study, one global ESN model enriched with FP-Growth association features (ESN+FP) and one global LSTM model with FP-Growth (LSTM+FP) were trained simultaneously using the sales data of 43 SKUs. Both models share cross-product parameters, representing a real-world scenario in multi-SKU retail where practitioners tend to apply a centralized model. However, performance evaluation was conducted at the per-item (per SKU) level using MAE and sMAPE metrics, so that it could be observed how a single global architecture reacted to different sales time series characteristics. Table 1 presents the MAE and sMAPE values of ESN+FP and LSTM+FP for each SKU. Using the smallest sMAPE as the selection criterion, it can be seen that ESN+FP provides the lowest error in 28 of the 43 SKUs, while LSTM+FP performs better in 15 SKUs. For some products such as Chitato, Me Lewis, Sari Roti, and Boncabe, the sMAPE value of ESN+FP is very small (often below 5%), while LSTM+FP produces a larger error. Conversely, for products such as Madu, Indomie, and several dairy products, LSTM+FP produces a lower sMAPE than ESN+FP, indicating that the LSTM architecture is better able to follow the demand dynamics in these time series. There are also several SKUs with very high sMAPE for both models (e.g., ABC Mie and Kecap Ikan dan Inggris), indicating time series with highly irregular and unpredictable demand patterns.

Table 1: Comparison of per-SKU performance between ESN+FP and LSTM+FP based on MAE and sMAPE.

| Item                    | ESN+FP Growth |              | LSTM+FP Growth |              |
|-------------------------|---------------|--------------|----------------|--------------|
|                         | MAE           | sMAPE (%)    | MAE            | sMAPE (%)    |
| CHITATO                 | 0.1           | 0.07         | 89.03          | 3.92         |
| ME LEWIS                | 2.46          | 1.05         | 16.39          | 4.11         |
| BREAD CRUMBS            | 3.74          | 1.47         | 39.42          | 5.38         |
| BONCABE                 | 1.05          | 1.79         | 63.87          | 6.52         |
| AJOMOTO SAUCE AND MICIN | 1.65          | 3.82         | 11.79          | 9.36         |
| NUTRISARI               | 4.45          | 4.13         | 41.11          | 9.78         |
| Sesame Oil and Samin    | 4.45          | 4.33         | 18.17          | 12.15        |
| French fries            | 1.84          | 4.5          | 22.22          | 13.85        |
| ROYCO                   | 2.39          | 5.79         | 12.10          | 18.89        |
| ULTRA MILK              | 58.42         | 7.88         | 42.27          | 18.99        |
| SEDAAP NOODLES          | 10.89         | 8.68         | 11.93          | 19.26        |
| SASA                    | 7.99          | 9.99         | 22.55          | 19.91        |
| ABC Sambal              | 6.08          | 10.3         | 19.03          | 24.06        |
| BANGO SOY SAUCE         | 9.17          | 11.59        | 25.17          | 24.41        |
| SOLUTION                | 15.92         | 11.7         | 11.53          | 25.20        |
| ONION                   | 19.31         | 11.72        | 76.23          | 25.87        |
| ROMA                    | 15.19         | 11.79        | 44.31          | 26.67        |
| RICE                    | 45.26         | 12.3         | 22.93          | 27.31        |
| GOOD DAY                | 16.24         | 12.34        | 11.75          | 27.72        |
| LEMONILO                | 13.99         | 12.55        | 23.62          | 29.59        |
| GARUDA                  | 6.83          | 13.77        | 62.02          | 30.18        |
| INDOMIE                 | 309.9         | 14.97        | 93.82          | 32.99        |
| MASAKO                  | 8.16          | 15.28        | 23.22          | 33.59        |
| AMO SPARK               | 15.09         | 15.97        | 51.72          | 34.63        |
| COCONUTS                | 45.18         | 17.37        | 25.45          | 34.75        |
| INDOFOOD                | 65.74         | 17.92        | 57.11          | 35.46        |
| BLUE BAND               | 19.11         | 19.1         | 44.11          | 37.05        |
| ABC Soy Sauce           | 7.83          | 19.36        | 40.22          | 37.73        |
| INDOMILK                | 28.79         | 19.6         | 40.27          | 38.67        |
| Bird's Nest Noodles     | 203.45        | 24.06        | 52.18          | 39.80        |
| KARA                    | 27.64         | 26.5         | 24.78          | 40.70        |
| KIS                     | 31.13         | 27.65        | 71.73          | 41.62        |
| Corn Flakes             | 29.36         | 29.02        | 125.66         | 42.41        |
| Flag Milk               | 69.08         | 30.97        | 28.72          | 42.63        |
| SAORI SAUCE             | 19.89         | 33.35        | 23.05          | 42.67        |
| CHIKI                   | 41.48         | 34.64        | 24.13          | 43.05        |
| SAJIKU SPICE FLOUR      | 20.35         | 35.2         | 43.72          | 45.37        |
| MILO                    | 69.82         | 41.91        | 62.46          | 46.02        |
| SARIMI                  | 24.99         | 52.07        | 55.60          | 47.00        |
| HONEY                   | 39.04         | 73.68        | 67.05          | 48.23        |
| GAGA NOODLES            | 27.27         | 78.2         | 34.89          | 49.52        |
| Fish Sauce and English  | 45.51         | 150.45       | 134.86         | 52.69        |
| ABC NOODLES             | 29.28         | 200          | 26.50          | 76.26        |
| <b>Average</b>          | <b>42.76</b>  | <b>30.84</b> | <b>33.15</b>   | <b>26.48</b> |

Source: Authors, (2026).

The pattern in Table 1 shows strong heterogeneity. For some items such as CHITATO, ME LEWIS, SARI ROTI, and BONCABE, ESN+FP achieved sMAPE below 5%, while LSTM+FP lagged significantly behind. This indicates that the combination of ESN reservoir with FP-Growth association features is very effective for the time series of these products. Conversely, there are other items such as MADU, ABC MIE, or several dairy products where LSTM+FP produces a lower sMAPE than ESN+FP, and ESN+FP tends to experience a significant under/over-prediction bias. There are also extreme cases such as ABC MIE and KECAP IKAN DAN INGGRIS where the sMAPE of ESN+FP is very high (up to around 200% and 150%), while LSTM+FP, although not good, remains within a more moderate error range. As shown in the Average row of Table 1, LSTM+FP achieves slightly lower mean MAE and sMAPE than ESN+FP. This indicates that, in aggregate across all SKUs, the global LSTM+FP model tends to produce smaller average errors. However, ESN+FP is more often the best model at the item level (28 SKUs), and its sMAPE value distribution is wider. This means that ESN+FP is very effective for certain SKU subsets but also shows high performance variation, while LSTM+FP is less often the best for a product, but its behavior is relatively more consistent and less likely to produce extreme errors. These item-level findings confirm that a single global model will not behave uniformly across all products, as it reacts differently to the time series characteristics of each SKU—ranging from volatility levels, trend patterns, to demand properties that are more continuous or sporadic—so performance evaluation should not rely solely on aggregate average values, but must always be reviewed at the SKU level.

In addition, the comparison results show that ESN+FP does indeed more often emerge as the model with the smallest sMAPE and is therefore worth considering as a global baseline, but LSTM+FP cannot be ignored because for some SKUs it actually provides more accurate predictions, so that in practice the combination of the two opens up opportunities for an adaptive model selection approach per product.

## IV.2 ITEM FORECASTING RESULT ANALYSIS

This subsection examines six representative SKUs selected to reflect diverse demand characteristics and compares models using both aggregate accuracy (MAE, sMAPE) and operational behavior at the final forecast point. The first lens is aggregate performance, which is measured by MAE and sMAPE throughout the test horizon. The second lens is operational performance, namely the behavior of the model at the last forecasting point and its suitability with the direction of demand change (up or down) towards the end of the period. The six pairs of graphs in Fig. 1–Fig. 6 were selected to represent three main patterns that emerged from the data: (i) cases where ESN+FP clearly outperformed LSTM+FP, (ii) cases where LSTM+FP was more accurate than ESN+FP, and (iii) cases where both models failed to represent demand dynamics (*hard-to-forecast series*). This dual-lens approach allows for a more balanced evaluation between average numerical accuracy and the practical usefulness of forecasting results at the item level.

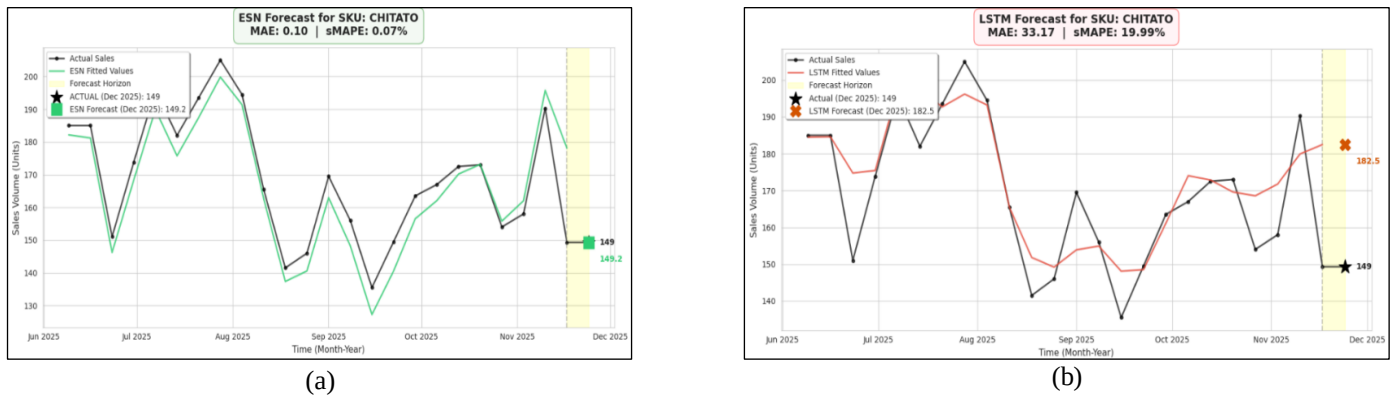


Figure 3: Comparison of CHITATO SKU sales forecast results between (a) ESN+FP and (b) LSTM+FP.

Source: Authors, (2026).

In Figure 3, both lenses consistently support the superiority of ESN+FP. From an aggregate perspective, ESN+FP produces an MAE of 0.10 and an sMAPE of 0.07%, which is much smaller than LSTM+FP, which has an MAE of 33.17 and an sMAPE of 19.99%. Operationally, the ESN+FP endpoint prediction in December 2025 closely matched the observed value (149 vs. 149.2) and captured short-term fluctuations. LSTM+FP tends to smooth out variations and slightly deviate from the actual line, resulting in less accurate form and value.

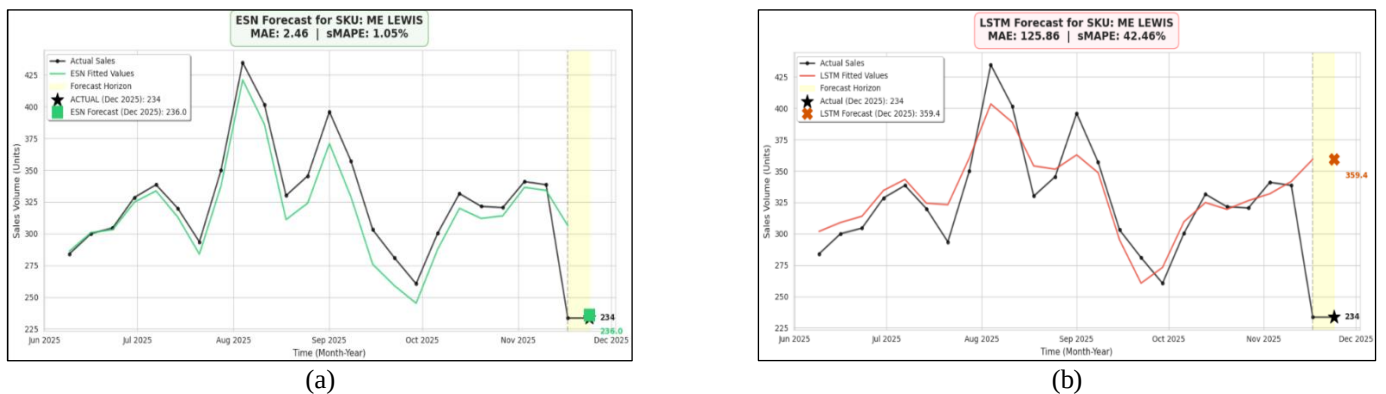
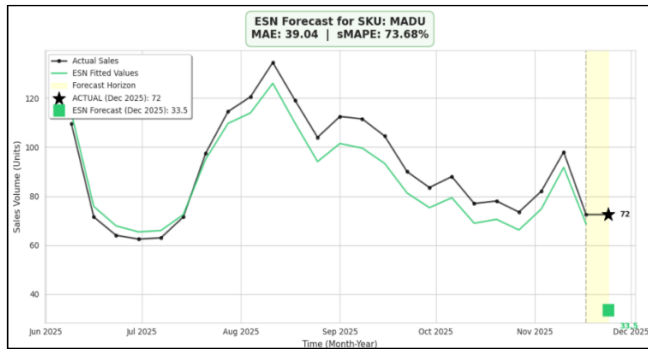


Figure 4: Comparison of sales forecast results for SKU ME LEWIS between (a) ESN+FP and (b) LSTM+FP.

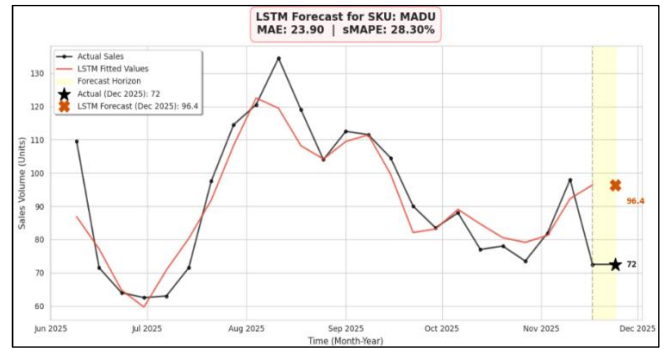
Source: Authors, (2026).

Figure 4 (SKU ME LEWIS) shows the same pattern. In aggregate, ESN+FP again excels with MAE of 2.46 and sMAPE of 1.05%, while LSTM+FP records MAE of 125.86 and sMAPE of 42.46%. From an operational perspective, ESN+FP provides a final prediction that is very close to the actual (234 vs. 236), with a curve shape that follows the ups and downs of sales. LSTM+FP not only has a large average error, but also predicts an overly high final level (359.4), making it unreliable for stock decision-making. These two examples illustrate the "fluctuating with clear local repetition" pattern group, where ESN+FP excels both in terms of metrics and final prediction behavior. The opposite is seen in Figure 5 and Figure 6, which represent series with relatively smooth trends and seasonality. In Figure 3 (HONEY SKU), from an aggregate perspective, LSTM+FP is clearly better with an MAE of 23.30 and sMAPE of 28.30%, compared to ESN+FP which has an MAE of 39.04 and sMAPE of 73.68%. Operationally, the final prediction of LSTM+FP (98.4) is still off from the actual 72, but its deviation ( ) is still smaller than that of ESN+FP, which predicted 33.5. The shape of the LSTM+FP curve is also more stable in following the downward trend in the latter half of the horizon, while ESN+FP shows a significant level bias.

In Figure 4 (INDOMIE SKU), the difference between the two models is even more apparent. LSTM+FP produced an MAE of 102.91 and an sMAPE of 4.52%, while ESN+FP recorded an MAE of 309.90 and an sMAPE of 14.97%. At the end point, the LSTM+FP prediction (2327.9) is much closer to the actual 2235 than ESN+FP (1915.1), and the LSTM+FP curve follows a relatively smooth upward trend, while ESN+FP fails to maintain its level. For a pattern like this—"smooth trend with weak seasonality"—both lenses point to LSTM+FP as the more suitable model.

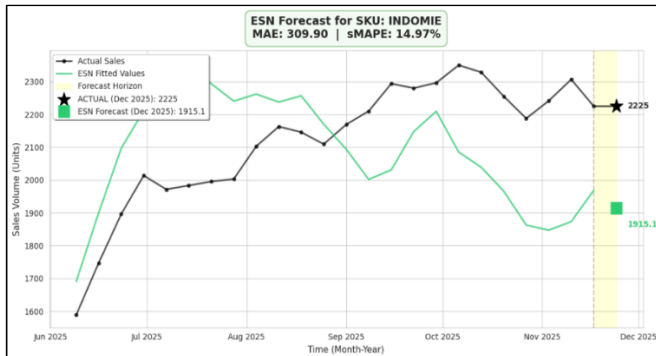


(a)

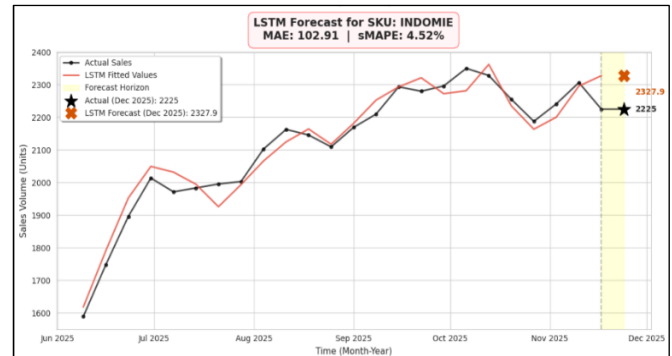


(b)

Figure 5: Comparison of MADU SKU sales forecast results between (a) ESN+FP and (b) LSTM+FP.  
Source: Authors, (2026).



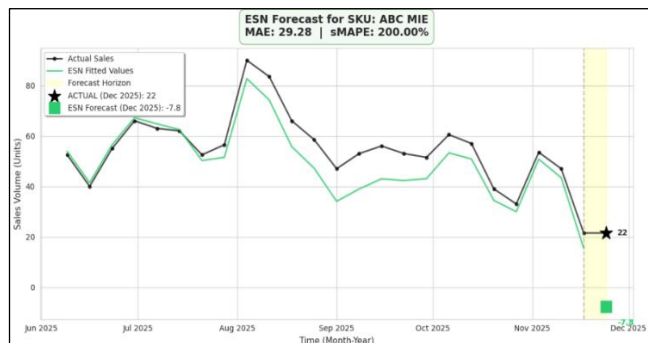
(a)



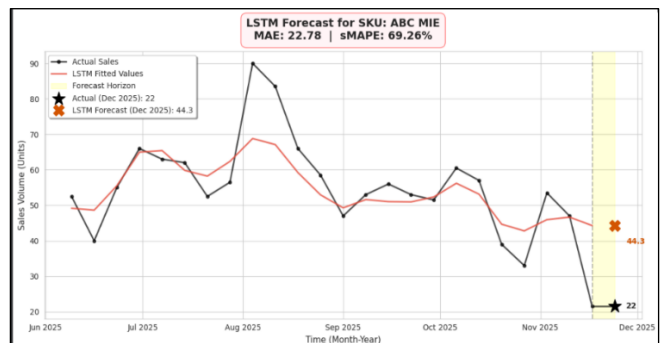
(b)

Figure 6: Comparison of sales forecast results for INDOMIE SKUs between (a) ESN+FP and (b) LSTM+FP.  
Source: Authors, (2026).

Figure 7 (SKU ABC MIE) and Figure 8 (SKU KECAP IKAN DAN INGGRIS) illustrate series that can be categorized as hard-to-forecast series. In Figure 5, the ABC MIE series shows sharp changes and extreme declines at the end of the horizon. In aggregate, LSTM+FP performs better (MAE 22.78; sMAPE 69.26%) than ESN+FP (MAE 29.28; sMAPE 200.00%), but both sMAPE values are equally high. From an operational perspective, the final prediction of ESN+FP (7.8) is slightly closer to the actual 22 than LSTM+FP (44.3), but both are clearly off and misread the magnitude of the decline in demand. In Figure 6, the SKU KECAP IKAN DAN INGGRIS shows a sporadic demand pattern with fluctuating levels. LSTM+FP is better in aggregate (MAE 31.88; sMAPE 46.24%) than ESN+FP (MAE 45.51; sMAPE 150.45%), and also provides a relatively closer final prediction (84.9 vs. actual 53 compared to 7.5 for ESN+FP). However, from an operational perspective, both models remain inadequate because the deviation at the end point is still large and the direction of level changes is not captured well.

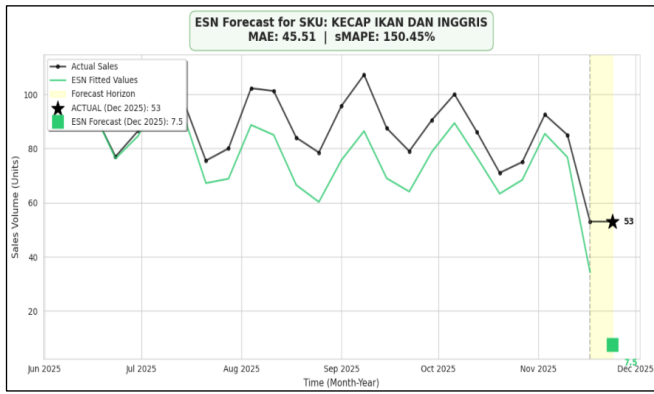


(a)

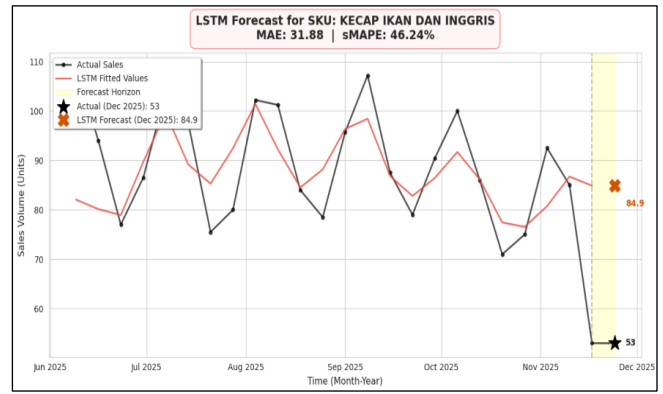


(b)

Figure 7: Comparison of ABC MIE SKU sales forecast results between (a) ESN+FP and (b) LSTM+FP.  
Source: Authors, (2026).



(a)



(b)

Figure 8: Comparison of sales forecast results for SKU KECAP IKAN DAN INGGRIS between (a) ESN+FP and (b) LSTM+FP.  
Source: Authors, (2026).

From the six examples in Figures 3–8, it can be concluded that the two assessment lenses provide complementary insights. For SKUs with **fluctuating but repeating** patterns, ESN+FP tends to excel in terms of both MAE/sMAPE and in replicating the shape and end point of the series. For SKUs with **smoother trends and seasonality**, LSTM+FP is more accurate, both in terms of aggregate error and the closeness of the final prediction to the actual value. Meanwhile, for series with **highly sporadic and unstructured demand**, both of these global models show limitations in terms of both numerical and operational aspects. This pattern-based insight confirms that an effective multi-SKU forecasting strategy needs to evaluate models from two perspectives—aggregate and operational—and encourages the use of an adaptive model selection approach tailored to the time series characteristics of each product group.

#### IV.3 RELATIONSHIP WITH TIME SERIES CHARACTERISTICS

The findings in Table 1 and the visual analysis in Figures 3–8 show that the performance of ESN+FP and LSTM+FP is greatly influenced by the time series characteristics of each SKU, not just by the model architecture used. Qualitatively, the sales time series of the 43 SKUs can be grouped into three main patterns: (i) a fluctuating pattern with clear local repetitions, (ii) a relatively smooth trend and seasonal pattern, and (iii) a highly sporadic and unstructured demand pattern. Each group exhibits different model tendencies in terms of aggregate performance (MAE/sMAPE) and operational behavior (final predictions and the direction of demand changes). In the first group, namely series with sharp but repetitive fluctuations (e.g., CHITATO, ME LEWIS, SARI ROTI, BONCABE), sales tend to oscillate around a certain level with several repeated spikes and declines over time. For these characteristics, ESN+FP generally provides the best performance: sMAPE values are in the very low range (often below 5%), and the ups and downs of the predictions closely follow the actual series. This indicates that the ESN reservoir effectively absorbs short-term dynamics and local variations, while the FP-Growth association feature helps add context to relevant inter-product relationships during periods of high demand. The second group includes series with long-term trends and subtle seasonality (such as MADU and INDOMIE). In these series, local fluctuations are relatively smaller than global trend changes, and there are no strong short-term pattern repetitions. Experiments show that LSTM+FP tends to be superior in this group: LSTM+FP produces lower MAE and sMAPE and is able to place the trend level and direction more accurately, while ESN+FP often experiences level bias that causes large vertical deviations even though the curve shape appears to follow the trend at first glance.

This is consistent with the character of LSTM, which is designed to capture long-term dependencies, making it more suitable for series with strong trend structures and gradual level changes. The third group consists of series with highly sporadic and unstructured demand, which is clearly seen in ABC MIE and KECAP IKAN DAN INGGRIS. Series in this group are characterized by sharp variations, high zero frequency, or sudden changes without seasonal patterns or stable trends. In this case, both global models show limitations: sMAPE reaches very high values and the final predictions are often far from the actual values. The FP-Growth association feature is also not very helpful, because the co-purchase patterns for these products tend to be unstable, making them difficult to use as additional signals. These series can be categorized as hard-to-forecast series that require a special approach beyond the ESN+FP and LSTM+FP configurations used in this study. In summary, the relationship between time series characteristics and the models that tend to excel can be summarized as follows: ESN+FP is suitable for SKUs with high but patterned volatility, LSTM+FP is more suitable for SKUs with smooth trends and seasonality, while SKUs with highly sporadic demand patterns are not suitable for modeling with only these two approaches. This pattern-based mapping forms the basis for model selection strategy recommendations in the multi-SKU context discussed in the next subsection.

#### IV.4 PRACTICAL IMPLICATIONS FOR MULTI-SKU RETAIL

From a practical perspective, findings from 43 SKUs indicate that applying a single global model to the entire product portfolio does not yield optimal results. Differences in demand pattern characteristics cause ESN+FP and LSTM+FP to be mutually superior in different SKU groups, and in a small portion of SKUs, both are equally inadequate. Therefore, forecasting strategies in a multi-SKU retail environment need to be designed as a step-by-step process that incorporates time series character diagnosis and adaptive model selection. First, before mass modeling, retailers are advised to conduct an initial diagnosis of the time series for each SKU based on simple indicators such as the volatility level (e.g., the ratio of standard deviation to average), the presence of trends and seasonality, and the level of intermittency (the proportion of periods with zero or very low demand).

This diagnosis can be used to group SKUs into three pattern types identified in Subsection IV.3: patterned-fluctuating, smooth-trending, and sporadic. Second, the results of the diagnosis can be mapped to model selection policies. For SKU groups with fluctuating but repeating patterns, ESN+FP can be used as the main baseline because it has proven to be superior in terms of both MAE/sMAPE and forecasting pattern suitability, especially when inter-product association information is relevant. For SKUs with smoother trends and seasonality, LSTM+FP is more appropriate to prioritize because it provides more accurate estimates of the level and direction of demand changes in aggregate. Meanwhile, SKUs with highly sporadic demand should not immediately rely on global ESN or LSTM models, but should consider using special methods for intermittent demand (e.g., Croston-based approaches) or be handled with more conservative stock policies until more suitable models are developed. Third, practical implementation in retail information systems can adopt a model selection framework per SKU. In this framework, the forecasting pipeline consists of: (i) a time series analysis module that periodically classifies SKUs, (ii) a model selection module that decides whether ESN+FP, LSTM+FP, or another method is used for a particular SKU, and (iii) a continuous evaluation module that monitors MAE/sMAPE and operational indicators such as bias level and accuracy of demand change direction. This framework allows retailers to leverage the strengths of each model without losing the scale and efficiency of a global approach. Thus, the results of this study not only provide empirical contributions in comparing ESN+FP and LSTM+FP, but also offer practical guidance for designers of multi-SKU sales forecasting systems. The approach that combines time series character diagnosis, adaptive model selection, and dual-lens evaluation (aggregate and operational) has the potential to improve forecasting accuracy as well as the business relevance of decisions made based on model output.

## V. CONCLUSIONS

This study shows that the integration of FP-Growth-based cross-product features can be operationally measured for multi-SKU retail sales forecasting through two different sequence architectures, namely ESN and LSTM, in a global model scheme with per-SKU evaluation on weekly time series. Experiments on 43 SKUs show that ESN+FP provides the best performance based on sMAPE on 28 of the 43 SKUs, while LSTM+FP excels on 15 SKUs, confirming that model superiority depends on series characteristics and cannot be concluded from a single aggregate metric. The discussion analysis reinforces practical mapping: ESN+FP tends to be suitable for volatile but still patterned SKUs, while LSTM+FP is more suitable for SKUs with smoother trends/seasonality because it is more stable in placing the level and direction of change, while highly sporadic SKUs remain hard-to-forecast and require a special approach beyond these two global model configurations. The practical implication is that adopting a single modeling approach for all SKUs is suboptimal; it is necessary to select models adaptively based on series characteristics and operational objectives. This study recommends a forecasting pipeline that incorporates series character diagnosis, per-SKU adaptive model selection (ESN+FP vs. LSTM+FP vs. other methods), and continuous evaluation using MAE/sMAPE and operational indicators (e.g., level bias and directional accuracy) to make stock decisions more business-relevant.

## VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** Ayu Manik Dirgayusari.

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**Investigation:** Made Leo Radhitya and I Made Subrata Sandhiyasa.

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**Writing – Review and Editing:** Ayu Manik Dirgayusari and Made Leo Radhitya.

**Resources and Software:** I Made Subrata Sandhiyasa, and Ketut Gde Manik Karvana.

**Supervision:** Ayu Manik Dirgayusari and I Made Dwi Putra Asana.

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