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IMPROVING DEMAND FORECASTING FOR CONSUMER HEALTH PRODUCTS USING CLUSTERED LSTM MODELS

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ABSTRACT

The study aims to enhance forecasting accuracy in a company's diverse product environment, focusing on two key objectives. First, this study aims to distinguish between clustered and non-clustered products in terms of forecast precision. Second, it investigates the possibility of utilizing aggregated forecasting models to more precisely predict product demand. Through clustering similar items and employing Long Short-Term Memory (LSTM) models, a notable improvement in demand forecasting accuracy was observed. Utilizing two years of consumer health product data and employing K-Means clustering, LSTM models tailored for each cluster outperformed non-clustered methods. Among 59 products grouped into 4 clusters, 20 demonstrated high (0-25% MAPE) and moderated (25-50% MAPE) forecast accuracy, surpassing only 9 products achieving similar precision without clustering. Further investigation into forecasting consumer health product demand is recommended. Additionally, the study explores the potential of creating aggregated forecasting models for efficiently predicting demand across multiple items.

Keywords: *Demand forecasting, LSTM models, Time-Series Forecasting, Clustering, Supply Chain Management)*

1. INTRODUCTION

Efficient inventory management is crucial for the distribution and logistics industry to ensure timely product availability and cost optimization [1]. However, consumer health product companies often face challenges due to inaccurate demand forecasting and declining demand, leading to excessive inventory storage costs and stockouts [2]. To address these issues, this study proposes a novel approach that combines clustering, specifically the K-Means Clustering method, with time series forecasting techniques like deep learning application (LSTM), aiming to optimize inventory management in the consumer health product industry and enhance demand forecasting accuracy [3].

The primary problem addressed in this study is suboptimal inventory management practices resulting from inaccurate demand forecasting and market uncertainties. By leveraging clustering and time series forecasting, our approach offers tailored forecasting models for different clusters of consumer health products, improving forecasting accuracy, and minimizing inventory costs. Although similar techniques have shown benefits in other industries [4], their application in the consumer health product sector remains relatively unexplored, making this study innovative and valuable.

This study aims to provide new insights into demand patterns, leading to improved inventory management practices. The findings will foster innovation in inventory management strategies for consumer health product companies, contributing to more effective supply chain management and improved customer satisfaction [5]. The main objectives of this study are to cluster consumer health products using the K-Means Clustering method, predict future demand using time series forecasting methods, specifically the Long Short-Term Memory (LSTM) approach, compare the accuracy and performance of different clustering approach, and provide recommendations for the most suitable forecasting method to optimize inventory management in the consumer health product industry.

The decision to leverage clustering as the initial step in the approach is driven by the heterogeneous nature of consumer health products, which exhibit diverse demand patterns and characteristics. By clustering comparable products, distinct clusters are formed [4][6], allowing the development of specific forecasting models for each cluster as opposed to the creation of separate models for each individual item. This streamlines the forecasting process and reduces computational complexity, leading to more efficient demand forecasts. Furthermore, the integration of the LSTM time series forecasting model allows capturing nonlinear patterns and long-term dependencies in the demand data of each cluster.

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2. RELATED RESEARCH

Previous research on integrating clustering for forecasting has predominantly employed time series data, representing a sequential arrangement of observations ordered chronologically. Time series analysis serves as a widely adopted forecasting methodology, involving the exploration of patterns between the variable being predicted and the temporal element [7]. The significance of enhancing accuracy in time series forecasting is emphasized by Hyndman and Athanasopoulos [8], who advocate a comprehensive strategy encompassing data pre-processing, model selection, feature refinement, hyperparameter tuning, and ensemble techniques.

To enhance precision in time series forecasting, Mostafa and Amano [4] investigated the effectiveness of clustering in optimizing forecasting models. Their study yielded substantial improvements in key metrics, including RMSE (Root Mean Square Error) and the coefficient of determination R-squared (R2), signifying heightened model accuracy. Building on these insights, this present study adopts a pre-forecasting clustering approach tailored to the diverse demand patterns inherent in the consumer health products domain.

By analyzing sales patterns, K-Means, which was enhanced by Subhan, Faqih, and Irawan [9], classifies products effectively, as demonstrated in 'Clustering Item Fast Moving and Slow Moving on Unilever Products.' Studies by Risnawati and Rohminatin [10] and Nasyuha, Zulham, and Rusydi [11] reinforce K-Means' ability to cluster products based on quantity proximity, regardless of scale. Forecasting involves predicting future events or conditions based on historical data and relevant factors [12]. It has applications in finance, marketing, manufacturing, and more, aiding decision-making [13]. Various methods, including linear regression, moving average, exponential smoothing, ARIMA, and LSTM, are used for time-series forecasting [8]. LSTM is particularly adept at handling complex sequential data with temporal dependencies, capturing trends and patterns [14]. In a comparative study by Ensafi et al. [15], neural networks like Stacked LSTM and CNN outperformed classical methods. Their study combines clustering and LSTM forecasting for improved demand forecasting and inventory management in consumer health products. It details the research approach, methodology, and performance evaluation, offering insights into their impact on accuracy. The results aim to provide practical recommendations for distribution firms to optimize inventory strategies, cut storage expenses, and avoid stockouts [16].

3. PROPOSED METHOD

To achieve the research objectives, a comprehensive methodology is adopted, consisting of the following steps:

3.1 Data Collection and Preprocessing

Analysis of historical demand and order data for consumer health products was followed by quality assurance preprocessing [17].

3.2 K-Means Clustering

The K-Means clustering method was used to categorize consumer health products according to their demand characteristics. K-Means algorithm formula consists of four steps: initialization of centroids, assignment of data points to clusters based on Euclidean distance, update of centroids by calculating means, and iterative convergence. The equation for calculating the Euclidean distance between data points and centroids followed [18]:

$$\mathrm{Distance}(\mathrm{x_i}, \mathrm{c_j}) = \sqrt{\sum_{\mathrm{k=1}}^{\mathrm{n}} (\mathrm{x_{i,k}} - \mathrm{c_{j,k}})^2} \qquad (1)$$

Where x_i represents the data point, c_j represents the centroid of cluster j, and n is the number of dimensions.

3.3 LSTM Models

LSTM, a type of recurrent neural network (RNN), is well-suited for time series forecasting due to its ability to handle long-term dependencies and irregular time intervals between data points. The LSTM architecture includes three main gates (forget, input, and output) and a cell state that facilitates learning long-term patterns. The formulas for each gate are as follows [19]:

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f \qquad (2)$$

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Input Gate:
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i \quad (3)$$
Forget Gate:
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o \quad (4)$$
Cell State Update:
$$C_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C \quad (5)$$

Where h_{t-1} is the previous hidden state, x_t is the current input, W_f, W_i, W_o, W_C are weight matrices, b_f, b_i, b_o, b_C are bias vectors, and σ is the sigmoid activation function. We present the LSTM formulas, describing their roles in processing sequential data and capturing temporal dependencies.

3.4 Aggregated Forecasting

To further improve forecasting accuracy, we proposed the concept of aggregated forecasting, where we aggregated individual item forecasts within each cluster. This process aims to leverage the inherent similarities between items within a cluster to generate more accurate and robust forecasts. The criteria for selecting the best clustering scenario and LSTM forecasting model are also discussed, providing insights into the selection process.

3.5 Proposed Method

The research method began with the accumulation and analysis of demand/order data for consumer health products from the past. This dataset was then preprocessed such as data cleansing, normalization, and feature selection to ensure data quality and suitability for subsequent analysis. The K-Means Clustering algorithm was then applied to the preprocessed data to group consumer health products with similar demand patterns, thereby producing distinct clusters. To identify the most effective basis for forecasting data, the clustering results were evaluated under various conditions, considering various combinations of features such as price and order.

After determining the optimal clustering scenario, the research developed forecasting models for each cluster using the Long Short-Term Memory (LSTM) method. LSTM models excel at identifying nonlinear patterns and long-term dependencies in time series data. For each cluster, demand data were aggregated into a single time series that served as input for the corresponding LSTM model. The trained LSTM models were then used to forecast the demand patterns of the future for each cluster.

To further improve the accuracy of the forecasting process, individual item-level forecasts within each cluster were aggregated to generate cluster-level demand forecasts that reflect the overall demand pattern for each cluster. This proposed method provides customized forecasting models for distinct clusters, resulting in more accurate predictions than conventional non-clustered methods. The performance of the method was evaluated using metrics such as Mean Absolute Percentage Error (MAPE) [20] to determine its efficacy in enhancing demand forecasting accuracy and inventory management effectiveness for consumer health product companies.

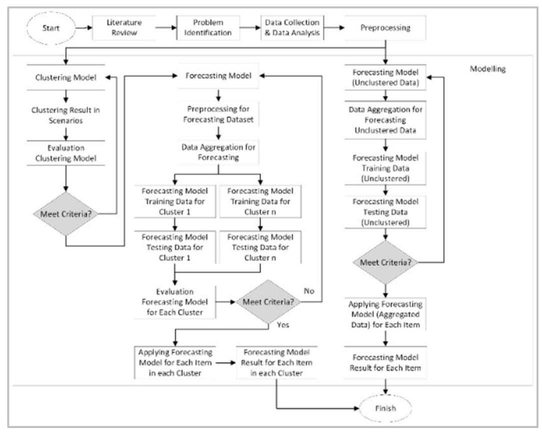

Figure 1: Research Design

4. RESULTS AND DISCUSSION

4.1 Dataset

This study uses a dataset consisting of 59 distinct consumer health product items. Each item is associated with crucial information such as price, order quantity (order_qty), and other relevant attributes. The data spans a two-year period, from January 2021 to December 2022, offering a comprehensive view of consumer health product demand patterns and trends.

4.2 Preprocessing

Before conducting the clustering analysis, essential preprocessing is carried out on the consumer health product dataset. Key features, apart from the dependent variable (order quantity), include price [21], discount, and DOI (days on inventory). Data cleaning, handling missing values, outliers, and normalization are performed to ensure data quality. The objective is to create a solid foundation for effective grouping of similar consumer health products based on consumer purchasing behavior. The mutual information scores [22] have been calculated to

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assess the relevance of the independent features to the target variable (likely consumer demand or purchasing behavior). The scores for each feature are as follows:

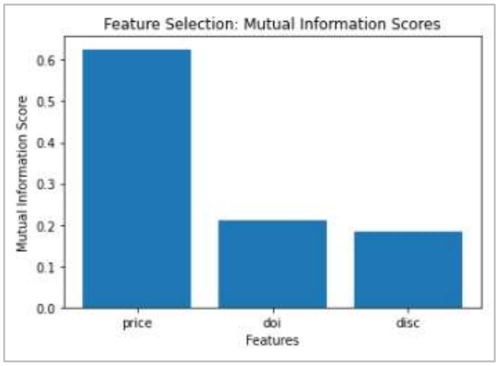

Figure 2: Feature Selection Result

The results show that price has the highest mutual information score, signifying a strong correlation with consumer behavior. Therefore, price is considered to play a very important role in the clustering process to group similar consumer health products based on their purchasing behavior. Although DOI and Disc also show significant scores, both show relatively weaker associations compared to price. The price and order data for 59 items have been combined into a unified dataset, which will be used for clustering in the next stage of analysis. The scenario for the next stage of clustering involves the following attribute combinations:

1. Utilizing the demand pattern attribute only (order_qty) for each Item over a monthly period spanning 24 months.
2. Utilizing the attributes of price pattern (price) and demand pattern (order_qty) for each Item over a monthly period spanning 24 months.

4.3 Clustering Analysis

The Gap Statistic method is used to determine the optimal number of clusters [23]. Based on the Gap values, the analysis suggests that 4 clusters are appropriate for the consumer health product dataset.

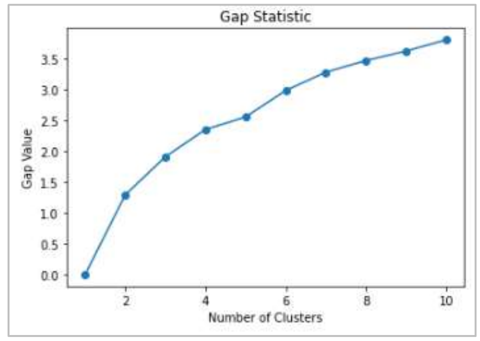

Figure 3: Cluster Determined

4.3.1 Clustering Scenario 1 - Using Only 'order_qty' Feature:

In this scenario, the dataset is clustered into 4 clusters based on the 'order_qty' feature alone. The Davies-Bouldin Index (DBI) [24] and Silhouette Score [25] are calculated to evaluate the clustering quality. The results show a DBI of 1.12 and a Silhouette Score of 0.53. The clusters have the following number of items: Cluster 0 (41 items), Cluster 1 (11 items), Cluster 2 (4 items), and Cluster 3 (3 items).

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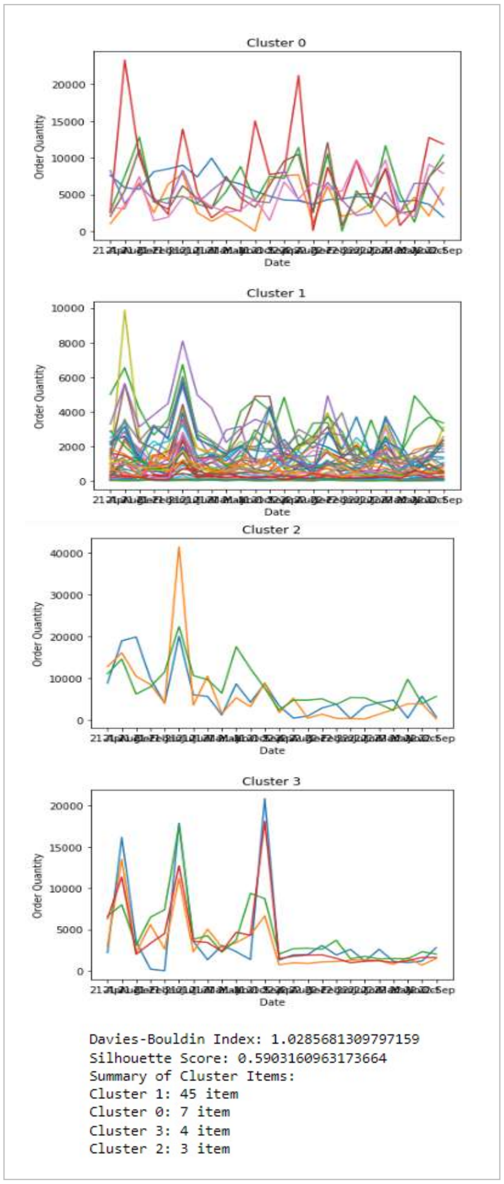

Figure 4: Clustering Result Scenario 1

In Figure 4, under scenario 1, Cluster 0 shows diversity with highly fluctuating demand patterns across its items. Cluster 1 also shows a fluctuating trend, where some items show increased demand or similar spikes during the first 5 months. Cluster 2 shows a similar pattern, except for one outlier with an increase in demand. Cluster 3 also shows a similar pattern, with a declining demand trend and stagnation in 2022. Also evident shows in the figure, items in clusters 0 and 3 have an order quantity scale value range up to 20,000 qty. Cluster 3 in general has a highest point range at 20,000 qty except for one item that has a maximum value approaching 40,000 qty. Only cluster 1 has an order quantity scale value range from 0 to 10,000 qty.

4.3.2 Clustering Scenario 2 - Using 'order_qty' and 'price' Features:

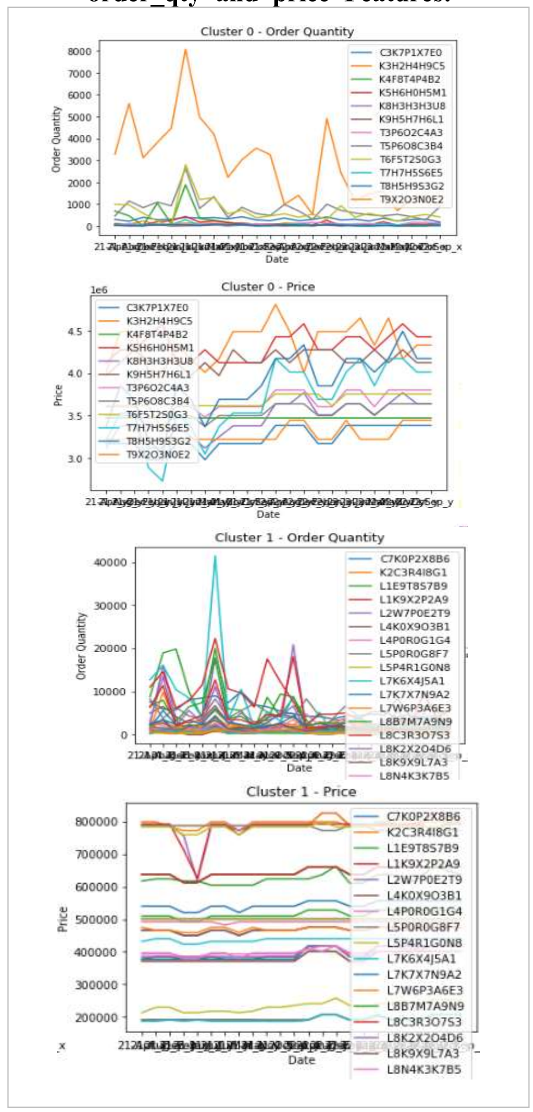

Figure 5: Cluster 0 & 1 in Clustering Result Scenario

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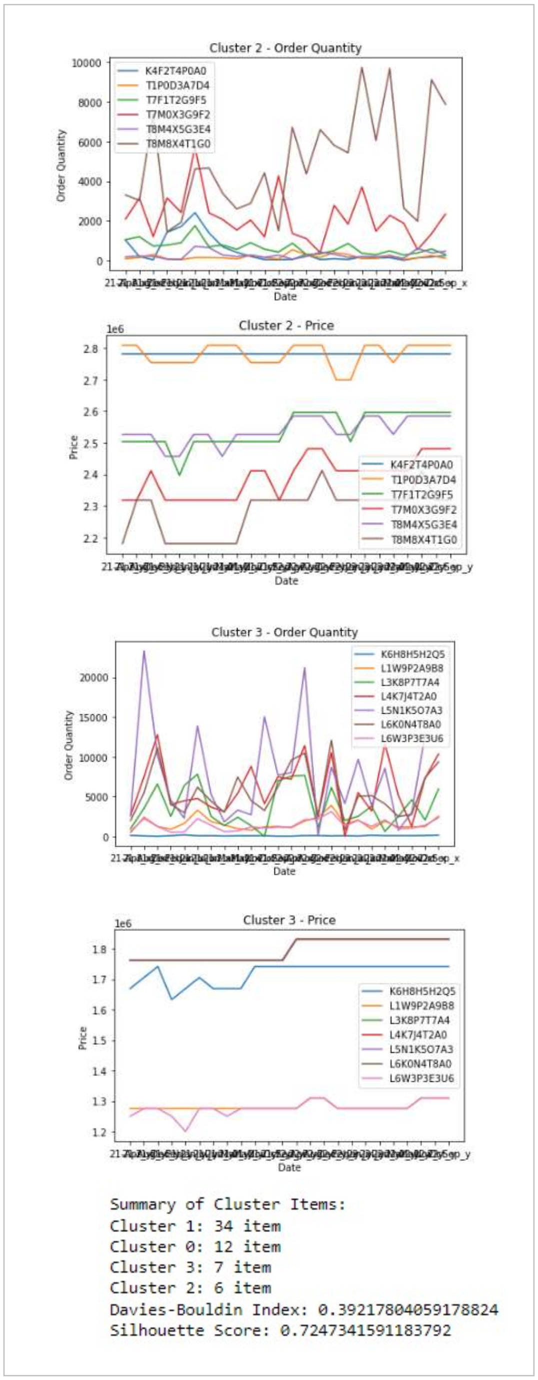

Figure 6: Cluster 2 & 3 in Clustering Result Scenario

In this scenario, the dataset is clustered using the features 'order_qty' and 'price'. DBI and Silhouette Score are calculated for evaluation. DBI has a value of 0.39, while Silhouette Score reaches 0.72. The cluster distribution looks as follows: Cluster 1 (34 items), Cluster 2 (12 items), Cluster 0 (7 items), and Cluster 3 (6 items).

The findings indicate consistent demand trends within Cluster 0, barring one outlier. Cluster 0 showcases fluctuating yet collectively rising price patterns. In Cluster 1, items display stagnant price trends and similar ordering behavior, marked by a mid-2021 spike. Clusters 2 and 3 exhibit fluctuating order patterns but differ in timing, with both showing an increasing price trend.

Overall, Scenario 1 and Scenario 2 align with similar order patterns, particularly within Cluster 1. The analysis reveals that Scenario 2, which uses both 'order_qty' and 'price' features, results in a lower Davies-Bouldin Index and a higher Silhouette Score, indicating better clustering quality compared to Scenario 1, which relies only on 'order_qty'. Additionally, the distribution of items among clusters varies between the two scenarios, showcasing the impact of including the 'price' feature in the clustering process

4.4 Forecasting Analysis

The dataset is prepared for forecasting by converting them to the desired format and aggregating them weekly. We separate the data for each cluster and the entire dataset. Then, we aggregate the data on a weekly basis for each cluster and the entire dataset for non-clustered data.

Table 1. Aggregated Forecasting Model Result (Using MAPE)

Cluster	MAPE	Accuracy
Cluster 0	87.22%	Low
Cluster 1	23.95%	High
Cluster 2	25.65%	High
Cluster 3	115.06%	Undefined
Non-clustered	22.64%	High

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The results in Table 1 show the Mean Absolute Percentage Error (MAPE) of the combined forecasting model, which highlights the different levels of accuracy between the clusters. Cluster 0 and Cluster 3 show lower accuracy, at 87.22% and 115.06% MAPE respectively, compared to Cluster 1 and Cluster 2 which have 23.95% and 25.65% MAPE respectively. The non-clustered dataset performed better with a MAPE of 22.64%. Since this study aims to assess the forecasting accuracy of individual items using the aggregate model, Table 2 in the conclusion of this study provides a more detailed breakdown of this accuracy. In addition, this table also presents a direct comparison with the results from the non-clustered model.

Clustered Model:

- High Forecast Accuracy: 8 items
- Moderate Forecast Accuracy: 12 items
- Low Forecast Accuracy: 8 items
- Undefined Forecast Accuracy: 31 items

Non-clustered Model:

- High Forecast Accuracy: 7 items
- Moderate Forecast Accuracy: 2 items
- Low Forecast Accuracy: 6 items
- Undefined Forecast Accuracy: 44 items

A comparison between the clustered and non-clustered models shows that out of 59 items, only 31 items cannot be predicted using the clustered aggregate data model. Of these 31, 20 items achieved high or medium accuracy. The clustered approach outperforms the non-clustered approach in terms of forecast accuracy, especially in the high and medium categories. Specifically, the clustered model successfully predicted 3 items with high accuracy and 10 items with medium accuracy, while the non-clustered model only predicted 2 items with high accuracy and 2 items with medium accuracy. Furthermore, the non-clustered model has 44 items with undefined prediction accuracy, while the clustered model has only 8 items with similar conditions. Figures 7.0 and 8.0 provide further analysis, while detailed results for each item are available in Table 2.

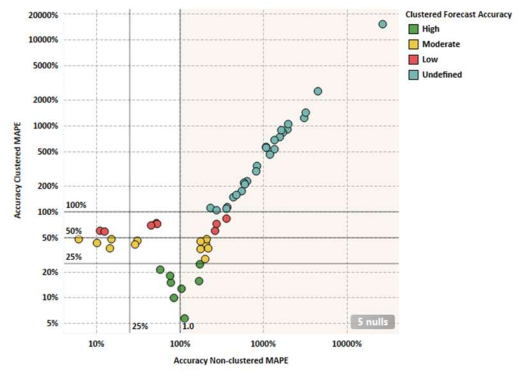

Figure 7: Comparison of MAPE for clustered vs. non-clustered aggregate forecasting

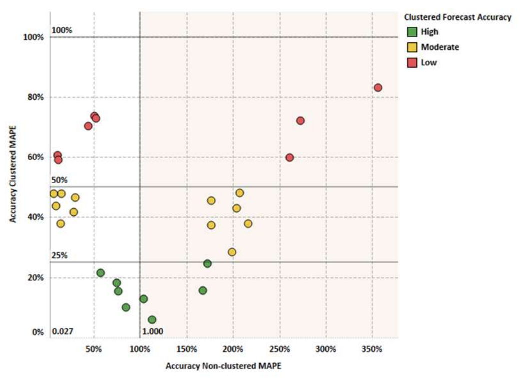

Figure 8: Comparison of MAPE for clustered vs. non-clustered excluding undefined result

The analysis presented in Figure 7 displays the prediction accuracy between the clustered model and the non-clustered model. The "undefined" items exhibit a similar pattern where the MAPE value exceeds 100%, rendering them unsuitable for forecasting models. In Figure 8, the comparison of prediction accuracy between the clustered and non-clustered models (excluding the "undefined" category) is illustrated. Items with low Clustered MAPE (representing high forecasting accuracy) tend to demonstrate differing and contrasting MAPE results in their Non-Clustered values. The majority of items with low Clustered MAPE (High Forecast Accuracy) have low accuracy values in their Non-Clustered MAPE. However, some items present moderate MAPE values in both metrics, indicating potential in their patterns for utilization in forecasting models.

Further analysis shows that, while there are some items that have the potential to improve prediction accuracy with the ungrouped model, there are more items with medium and high accuracy in forecasting associated with the

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grouped model (20 items compared to 9 items). If the Mean Absolute Percentage Error (MAPE) for unidentified items is equal to or greater than 100% adjusted for the 100% value in MAPE, then the average MAPE value for each item using these two methods is 72.55% average MAPE for the cluster method and 84.25% average MAPE for the non-cluster method. With a lower average MAPE for each item, these results indicate that the clustered method is able to accurately predict more item variations, reinforcing its advantage over the non-clustered method. The detailed data can be found on the last page of the paper in Table 2.

5. CONCLUSION

In conclusion, this study has achieved significant progress in improving demand forecasting accuracy for consumer health products. By combining the Long Short-Term Memory (LSTM) technique with data clustering, we successfully developed a robust forecasting model. The results of this study provide valuable insights and implications for the industry.

Our approach, which focuses on a clustered LSTM model, convincingly outperforms conventional non-clustered methods. Through careful item segmentation and the application of the customized LSTM model, we managed to achieve outstanding results. Specifically, we recorded high forecast accuracy (MAPE) for 9 items and moderate accuracy for 10 items in the clustered model. The analysis also identified areas of improvement for 20 items, while the other 20 items still showed unclear forecasting accuracy. This nuanced categorization underscores the precision and potential of our approach in predicting demand for different product groups. In contrast, the uncategorized model resulted in a relatively lower level of accuracy. With high forecast accuracy for only 7 items and moderate accuracy for 2 items, most of the dataset (6 items) experienced low forecast accuracy. Notably, the undefined accuracy range covers 44 items, which further strengthens the effectiveness of our clustered LSTM model.

This study has two implications. First, this study reconfirms the importance of advanced machine learning techniques, such as clustered LSTM models, in improving the accuracy of demand forecasting. In the consumer health products industry, the potential for informed decision-making and optimized supply chain management is obvious. Towards the end of this study, it is imperative to emphasize future growth areas. Resolving the issues of low forecasting accuracy and undefined results remains a top priority. These efforts are key to further refining and improving our forecasting methodology.

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REFERENCES

[1] A. Mitra, A. Jain, A. Kishore, and P. Kumar, “A Comparative Study of Demand Forecasting Models for a Multi-Channel Retail Company: A Novel Hybrid Machine Learning Approach,” *Oper. Res. Forum*, vol. 3, no. 4, p. 58, Sep. 2022, doi: 10.1007/s43069-022-00166-4.

[2] F. Azis and D. Ruhiat, “Model Persediaan Barang Deteriorasi dengan Exponential Declining Demand, Time-Varying Holding Cost dan Return,” *J. Ris. Mat. Dan Sains Terap.*, vol. 1, p. 12, Dec. 2021.

[3] Z. Liu, Z. Zhu, J. Gao, and C. Xu, “Forecast Methods for Time Series Data: A Survey,” *IEEE Access*, vol. 9, pp. 91896–91912, 2021, doi: 10.1109/ACCESS.2021.3091162.

[4] S. M. Mostafa and H. Amano, “EFFECT OF CLUSTERING DATA IN IMPROVING MACHINE LEARNING MODEL ACCURACY,” *J. Theor. Appl. Inf. Technol.*, vol. 97, no. 21, p. 2973, Nov. 2019.

[5] I. H. Santi and I. Guntarayana, “Effect Of Supply Chin Product Quality Prima Service Costumer Satisfaction And Loyality,” *J. Perilaku Dan Strategi Bisnis*, vol. 8, no. 2, p. 129, Aug. 2020, doi: 10.26486/jpsb.v8i2.1243.

[6] A. Wibowo and A. R. Handoko, “Segmentasi Pelanggan Ritel Produk Farmasi Obat Menggunakan Metode Data Mining Klasterisasi Dengan Analisis Recency Frequency Monetary (RFM) Termodifikasi,” *J. Teknol. Inf. Dan Ilmu Komput.*, vol. 7, no. 3, p. 573, May 2020, doi: 10.25126/jtiik.2020702925.

[7] J. E. Hanke and D. W. Wichern, *Business forecasting*, 9. ed., new International ed. Harlow: Pearson Education International, 2014.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[8] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*.

[9] A. Subhan, A. Faqih, and B. Irawan, "CLUSTERING ITEM FAST MOVING DAN SLOW MOVING PADA PRODUK UNILEVER MENGGUNAKAN ALGORITMA K-PROTOTYPE (Studi Kasus: YOGYA PURWAKARTA)," vol. 6, no. 2, 2022.

[10] Risnawati and Rohminatin, "K-MEANS CLUSTERING HWI PRODUCTS (Case Study: HWI Kisaran Distributor)," *Int. Conf. Soc. Sci. Inf. Technol.*, pp. 27–36, Aug. 2020.

[11] A. H. Nasyuha, Z. Zulham, and I. Rusydi, "Implementation of K-means algorithm in data analysis," *TELKOMNIKA Telecommun. Comput. Electron. Control*, vol. 20, no. 2, p. 307, Apr. 2022, doi: 10.12928/telkomnika.v20i2.21986.

[12] T. M. Mitchell, *Machine Learning*. in McGraw-Hill series in computer science. New York: McGraw-Hill, 1997.

[13] B. L. Bowerman, R. O'Connell, and A. Koehler, *Forecasting, time series, and regression: an applied approach (4th edition)*, 4th ed. Duxbury Press, 2005.

[14] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, Nov. 1997, doi: 10.1162/neco.1997.9.8.1735.

[15] Y. Ensafi, S. H. Amin, G. Zhang, and B. Shah, "Time-series forecasting of seasonal items sales using machine learning – A comparative analysis," *Int. J. Inf. Manag. Data Insights*, vol. 2, no. 1, p. 100058, Apr. 2022, doi: 10.1016/j.jjimei.2022.100058.

[16] J. E. Jarrett and Management Science and Finance, University of Rhode Island, Kingston, RI 02881, USA., "An Analysis of Lost Sales," *Manag. Econ. Res. J.*, vol. 01, p. 28, 2015, doi: 10.18639/MERJ.2015.01.159412.

[17] J. Hartono M, *Metoda Pengumpulan dan Teknik Analisis Data*. Penerbit Andi, 2018.

[18] M. Wahyudi, Masitha, R. Saragih, and Solikhun, "Data Mining Penerapan Algoritma K-Means Clustering dan K-Medoids Clustering," in *Data Mining Penerapan Algoritma K-Means Clustering dan K-Medoids Clustering*, in 1, no. 1. , 2020.

[19] A. Sherstinsky, "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network," *Phys. Nonlinear Phenom.*, vol. 404, p. 132306, Mar. 2020, doi: 10.1016/j.physd.2019.132306.

[20] G. P. Zhang, "Time series forecasting using a hybrid ARIMA and neural network model," *Neurocomputing*, vol. 50, pp. 159–175, Jan. 2003, doi: 10.1016/S0925-2312(01)00702-0.

[21] D. Armbruster, "Price Elasticity of Demand and Supply," in *Business Mathematics*, Springer, 2019, pp. 135–156.

[22] Hanchuan Peng, Fuhui Long, and C. Ding, "Feature selection based on mutual information criteria of max-dependency, max-relevance, and min-redundancy," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 27, no. 8, pp. 1226–1238, Aug. 2005, doi: 10.1109/TPAMI.2005.159.

[23] R. Tibshirani, G. Walther, and T. Hastie, "Estimating the Number of Clusters in a Data Set Via the Gap Statistic," *J. R. Stat. Soc. Ser. B Stat. Methodol.*, vol. 63, no. 2, pp. 411–423, Jul. 2001, doi: 10.1111/1467-9868.00293.

[24] A. A. Vergani and E. Binaghi, "A Soft Davies-Bouldin Separation Measure," in *2018 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE)*, Rio de Janeiro: IEEE, Jul. 2018, pp. 1–8. doi: 10.1109/FUZZ-IEEE.2018.8491581.

[25] P. J. Rousseeuw, "Silhouettes: A graphical aid to the interpretation and validation of cluster analysis," *J. Comput. Appl. Math.*, vol. 20, pp. 53–65, Nov. 1987, doi: 10.1016/0377-0427(87)90125-7.

[26] *formation Technology (EIT)*. Brookings, SD, USA: IEEE, May 20–22, 2019, pp. 063–068.

[27] J. Mittelstaedt, J. Wacker, and D. Stelling, "Effects of display type and motion control on cybersickness in a virtual bike simulator," *Displays*, vol. 51, pp. 43–50, 2018

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31st January 2024. Vol.102. No 2

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Table 2. Aggregated Forecasting Model Result by item

No.	Item Code	Cluster	Clustered MAPE	Clustered Forecast Accuracy	Non-clustered MAPE	Non-clustered Forecast Accuracy
1	T7H7H5S6E5	Cluster 0	9.95%	High	84.79%	Low
2	T8H5H9S3G2	Cluster 0	15.67%	High	168.06%	Undefined
3	T6F5T2S0G3	Cluster 0	43.71%	Moderate	10.00%	High
4	T3P6O2C4A3	Cluster 0	60.64%	Low	11.06%	High
5	C3K7P1X7E0	Cluster 0	83.14%	Low	355.96%	Undefined
6	K8H3H3H3U8	Cluster 0	105.75%	Undefined	271.17%	Undefined
7	T5P6O8C3B4	Cluster 0	226.13%	Undefined	628.04%	Undefined
8	T9X2O3N0E2	Cluster 0	1237.64%	Undefined	3066.32%	Undefined
9	K5H6H0H5M1	Cluster 0	1423.26%	Undefined	3217.57%	Undefined
10	K3H2H4H9C5	Cluster 0	inf%	Undefined	inf%	Undefined
11	K4F8T4P4B2	Cluster 0	inf%	Undefined	inf%	Undefined
12	K9H5H7H6L1	Cluster 0	inf%	Undefined	inf%	Undefined
13	L7W6P3A6E3	Cluster 1	21.46%	High	57.83%	Low
14	L8C3R3O7S3	Cluster 1	15.17%	High	76.53%	Low
15	T1C6R4F7A6	Cluster 1	12.84%	High	103.68%	Undefined
16	T3W8L6H1B5	Cluster 1	5.79%	High	113.26%	Undefined
17	T3C1R5F6C7	Cluster 1	24.43%	High	172.45%	Undefined
18	L4P0R0G1G4	Cluster 1	41.74%	Moderate	28.49%	Moderate
19	T8C6R0F4B3	Cluster 1	46.55%	Moderate	30.44%	Moderate
20	T2W0L2C1B9	Cluster 1	37.18%	Moderate	176.49%	Undefined
21	T5W4L9B9B5	Cluster 1	43.03%	Moderate	203.82%	Undefined
22	T2W9L1G9A9	Cluster 1	48.04%	Moderate	207.32%	Undefined
23	K2C3R4I8G1	Cluster 1	37.80%	Moderate	216.65%	Undefined
24	T2S2K8J2C8	Cluster 1	59.76%	Low	260.90%	Undefined
25	C7K0P2X8B6	Cluster 1	72.19%	Low	273.05%	Undefined
26	L2W7P0E2T9	Cluster 1	111.30%	Undefined	228.34%	Undefined
27	L1E9T8S7B9	Cluster 1	109.28%	Undefined	356.46%	Undefined
28	T3C1R1F0D2	Cluster 1	114.35%	Undefined	365.53%	Undefined
29	T9S1K4A1A0	Cluster 1	147.66%	Undefined	431.01%	Undefined
30	L5P0R0G8F7	Cluster 1	157.48%	Undefined	470.67%	Undefined
31	T8S6K8J7B3	Cluster 1	175.71%	Undefined	541.52%	Undefined
32	T4C4R7O5Z7	Cluster 1	220.16%	Undefined	582.69%	Undefined
33	L8K9X9L7A3	Cluster 1	211.28%	Undefined	596.24%	Undefined
34	L4K0X9O3B1	Cluster 1	296.23%	Undefined	808.56%	Undefined
35	T6S2K6J1A2	Cluster 1	344.79%	Undefined	827.15%	Undefined
36	L7K7X7N9A2	Cluster 1	562.92%	Undefined	1070.69%	Undefined
37	P1W9S6N6H6	Cluster 1	566.80%	Undefined	1075.24%	Undefined
38	T3S9K2J7R4	Cluster 1	467.27%	Undefined	1180.49%	Undefined
39	L1K9X2P2A9	Cluster 1	680.26%	Undefined	1339.15%	Undefined
40	L8B7M7A9N9	Cluster 1	742.53%	Undefined	1554.50%	Undefined
41	L5P4R1G0N8	Cluster 1	892.74%	Undefined	1640.68%	Undefined
42	L8K2X2O4D6	Cluster 1	849.95%	Undefined	1702.25%	Undefined
43	P3B8W8S3A0	Cluster 1	906.86%	Undefined	1916.67%	Undefined
44	L7K6X4J5A1	Cluster 1	1063.31%	Undefined	1977.39%	Undefined
45	L8N4K3K7B5	Cluster 1	2530.58%	Undefined	4495.95%	Undefined
46	L8W5H9K1C2	Cluster 1	inf%	Undefined	inf%	Undefined
47	T7F1T2G9F5	Cluster 2	28.45%	Moderate	199.28%	Undefined
48	T8M4X5G3E4	Cluster 2	47.91%	Moderate	15.10%	High
49	T8M8X4T1G0	Cluster 2	73.59%	Low	51.40%	Low
50	T1P0D3A7D4	Cluster 2	45.57%	Moderate	177.11%	Undefined
51	T7M0X3G9F2	Cluster 2	537.78%	Undefined	1342.59%	Undefined
52	K4F2T4P0A0	Cluster 2	inf%	Undefined	inf%	Undefined
53	K6H8H5H2Q5	Cluster 3	17.98%	High	75.39%	Low
54	L6W3P3E3U6	Cluster 3	47.86%	Moderate	6.08%	High
55	L3K8P7T7A4	Cluster 3	37.78%	Moderate	14.38%	High
56	L1W9P2A9B8	Cluster 3	59.02%	Low	12.32%	High
57	L4K7J4T2A0	Cluster 3	70.27%	Low	44.76%	Moderate
58	L6K0N4T8A0	Cluster 3	72.83%	Low	52.46%	Low
59	L5N1K5O7A3	Cluster 3	15362.17%	Undefined	26856.26%	Undefined
Average MAPE (*with adjusted MAPE)			Clustered Method	72.55%	Non-clustered Method	84.25%