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Sales forecasting of pet food at oyen petshop using the fuzzy time series–markov chain method

Agung Pratama[1] , Rakhmat Kurniawan[2]

[1,2]*Department of Computer Science, State Islamic University of North Sumatra, Indonesia*

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ABSTRACT

Oyen Petshop faces stock management inaccuracies because sales records are still kept manually, while demand patterns are highly fluctuating and difficult to predict, often leading to overstock or stockouts that harm the business. The purpose of this study is to develop a Fuzzy Time Series–Markov Chain (FTS-MC) model to forecast pet food sales at Oyen Petshop and implement it in the form of a website. The research method applies FTS-MC to construct fuzzy intervals, generate FLR/FLRG, calculate transition probabilities, and produce forecasts based on dry-food sales data from April 2024 to March 2025. The results show that the FTS-MC model achieves a MAPE of 8.92%, with forecasted values that follow actual fluctuations and indicate a stable demand trend of 206–224 units for the next seven periods. Black Box Testing confirms that all web-based system functions operate correctly and all test scenarios pass, ensuring the system is ready for operational use. The findings indicate that the system enables more precise stock estimation, supports the establishment of safe reorder limits, and allows procurement decisions to be made faster and more consistently without manual calculations.

Corresponding Author:

Agung Pratama,
Department of Computer Science,
Universitas Islam Negeri Sumatera Utara,
Jl. William Iskandar Ps. V, Medan Estate, Kec. Percut Sei Tuan, Kab. Deli Serdang, Sumatera Utara, 20371, Indonesia
Email: agungpratama0719@gmail.com

1. Introduction

Indonesia's economy, which is supported by the Micro, Small, and Medium Enterprises (MSME) sector with a contribution of more than 60% to the Gross Domestic Product (GDP) and employment of around 97%, shows that the stability of small businesses plays an important role in national economic sustainability (Anatan & Nur, 2023; Mohite et al., 2025). The IMF Country Report 2024 confirms that MSMEs contribute 61% to GDP and employ 97% of the workforce, accounting for 99% of all business units in Indonesia (Surorejo et al., 2024; Wahyu et al., 2025). The growth of the pet care industry in urban areas has further strengthened this demand, driven by an 88% increase in public interest in pets from January to September 2019, reaching a total of 419,000 searches in 2021 (Andriani & Anandianskha, 2023; Huang et al., 2025; Sari et al., 2025). Demand for pet food products has increased, especially in the cat food segment, where a Rakuten Insight survey in January 2022 showed that 47% of Indonesians prefer to keep cats rather than dogs (Ai et al., 2025; Wulandari et al., 2021). This high demand is accompanied by a major challenge for small businesses in predicting stock requirements, as sales patterns are fast-changing and unpredictable (Moura et al., 2024; Upadhyay et al., 2023). This

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uncertainty often leads to errors in inventory estimation, which affects capital utilization and service quality (Ese & Raphael, 2024; Fakhriyana & Brilliant, 2023; Feriyanto et al., 2024b).

This situation is evident in the operations of Oyen Petshop in Medan, which still relies on manual inventory tracking through a daily logbook (Feriyanto et al., 2024a; Ramadi et al., 2025; Sjofjan & Adli, 2022). This practice is common among micro businesses in Indonesia, especially since the adoption of digital technology among MSMEs is still a concern for the National Research and Innovation Agency (BRIN) due to its low rate, even though the government, through the Ministry of Communication and Information Technology, has set a target of 30 million MSMEs adopting digital technology by 2024 (Anatan & Nur, 2023; Kilay et al., 2022). Manual systems make it difficult for business owners to monitor changes in demand, which can lead to excess or shortage of stock (Moura et al., 2024; Olamide Raimat Amosu et al., 2024; Upadhyay et al., 2023). Both conditions have the potential to harm the business because goods may expire or customers may not get the products they need (Ese & Raphael, 2024; Olamide Raimat Amosu et al., 2024). This situation reflects a gap in practices that requires the implementation of a system capable of processing sales data more accurately and efficiently (Moura et al., 2024; Ramadi et al., 2025).

Various studies on sales forecasting have been conducted to address the need for more measurable stock provision. One of the studies referred to is a study by Yustin et al. (2023) which aims to model daily sales forecasting in a retail store and compare the accuracy of two variants of the Fuzzy Time Series model, namely the Cheng model and the Ruey Chyn Tsaur model, using historical sales data that is volatile in nature. The results of the study show that the Cheng model has a MAPE value of 9.904%, while the Ruey Chyn Tsaur model has a MAPE value of 14.01%, so the Cheng model is considered superior for the case studied. However, the study is still limited to manual calculations without producing a software-based system that can be used directly by business actors and has not been directed at micro-businesses such as pet shops. In addition, previous studies have not addressed the main challenge of highly fluctuating demand in micro-retail settings, where single Fuzzy Time Series models often fail to capture abrupt transitions between demand levels. Moreover, no prior work has integrated Fuzzy Time Series with probabilistic transition modeling such as Markov Chain to represent the likelihood of upward or downward movements between fuzzy states. These limitations indicate a clear research gap, particularly the absence of a hybrid approach capable of modeling both fuzzy uncertainty and state-transition probabilities for pet food demand characterized by rapid fluctuations.

To overcome the limitations of this research, a forecasting approach is needed that not only produces mathematical models but also presents these models in the form of systems that can be directly operated by business owners and are in line with the characteristics of fluctuating sales data (Moura et al., 2024; Ramadi et al., 2025; Stefana et al., 2024). The Fuzzy Time Series–Markov Chain approach is considered appropriate because Fuzzy Time Series is chosen to represent demand patterns that contain uncertainty and high levels of fluctuation, while Markov Chain provides an overview of the probability of changes in data over time based on the transition probability distribution (Devianto et al., 2022; Telaumbanua & Febrian, 2023). The urgency of combining both methods lies in the fact that single Fuzzy Time Series models only describe linguistic demand behavior but do not quantify how likely state changes occur, making them less effective when sudden increases or decreases appear in short and volatile datasets typical of micro-enterprises. By integrating Fuzzy Time Series with Markov Chain, the model becomes more responsive to sharp fluctuations because the transition probability matrix captures how often each fuzzy state shifts to another, allowing more stable and adaptive predictions. The integration of the two opens up opportunities to present a more stable forecasting model that can be applied to a website-based system that functions as a tool for inventory management in small businesses (Devianto et al., 2022; Mohite et al., 2025; Ramadi et al., 2025).

The purpose of this study is to develop a Fuzzy Time Series–Markov Chain model to forecast pet food sales at Oyen Petshop and implement it in the form of a website so that the forecasting results can be used practically by business owners. This research is expected to contribute to the development of time series forecasting science, particularly regarding the application of the combined Fuzzy Time Series–Markov Chain method on a small business scale engaged in pet food sales. From a practical standpoint, this research is expected to assist Oyen Petshop in improving inventory management, reducing the risk of losses due to inventory inaccuracies, and supporting a more measurable procurement decision-making process.

2. Method

Data Collection

Conducted through direct observation at Oyen Petshop to obtain sales patterns and fluctuations, as well as literature studies to collect relevant theories and research related to the Fuzzy Time Series method. The data obtained was in the form of dry cat food sales during April 2024-March 2025.

Data Analysis

Data analysis examined the fundamental characteristics of the dry cat food sales dataset for April 2024-March 2025, including the number of periods, minimum and maximum values, fluctuation patterns, and overall sales trends. This stage also involved initial preprocessing, which consisted of defining the universal set based on the dataset's extreme values, calculating the number and length of fuzzy intervals for interval partitioning, and ensuring that the resulting universal set was relevant and representative of actual sales conditions at Oyen Petshop.

Implementation of the FTS–MC Method

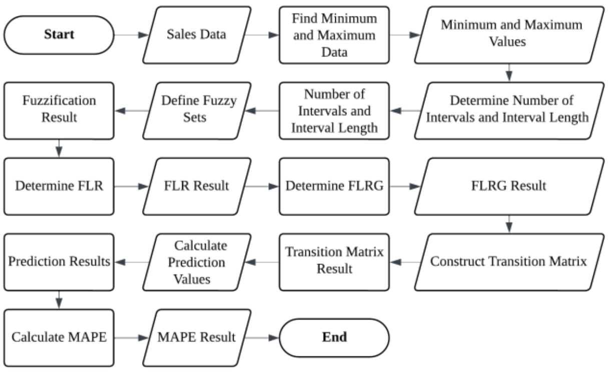

Figure 1 . Fuzzy time series markov chain flowchart

Fuzzy Time Series–Markov Chain (FTS-MC) was chosen as the forecasting method because it is capable of handling fluctuating and uncertain (ambiguous) sales data, and through its integration with Markov Chain, it can improve the accuracy of predicting historical data transition patterns. This method was evaluated using Mean Absolute Percentage Error (MAPE) with the formula $MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Yt-Ft}{Yt}\right| \times 100\%$ making its application relevant to the operational conditions of Oyen Petshop and supporting more efficient stock decision-making (Alyousifi et al., 2021; Sunusi et al., 2025).

a. Determining the universe set using the $U = [D_{min} - D1, D_{max} + D2]$ ....(1)
Determining the number of intervals using Sturges '$n = 1 + 3,322\log(N)$ ....(2)
Calculating the interval length using $l = \frac{(Dmax+D2)-(Dmin-D1)}{n}$ ....(3)

b. Forming FLR and FLRG as logical processes for grouping fuzzy state transitions $(Ai \rightarrow Aj)$.

c. Calculating the Markov transition probability matrix using the equation $Pij = \frac{Hij}{Hi}$ ....(4)

d. Calculating the initial prediction using the equation:
one-to-many $F(t) = m1Pj1 + m2Pj2 + \cdots + Y(t-1)Pjj + \cdots + mnPjn$ ....(5)
one-to-one $F(t) = mkPik = mk$ ....(6)

e. Calculate the final forecast using $F'(t) = F(t) \pm Dt1 \pm Dt2$ ....(7)
with basic adjustment $Dt1 = \pm\frac{1}{2}$ ....(8)
trend adjustment $Dt2 = \pm\frac{1}{2}s$ ....(9)

The adjustment values in equations (7)-(9) are determined based on the direction and magnitude of fuzzy-state transitions between the previous and current periods. Dt1 is applied when a

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one-step transition occurs, using half of the interval length $\left(\frac{L}{2}\right)$ as the adjustment unit, while Dt2 reflects multi-step transitions through the trend factor (s). Together, these adjustments increase the sensitivity of the final forecast by allowing $F'(t)$ to adapt to sudden changes in data patterns rather than relying solely on the initial forecast F(t), ensuring that the model remains responsive without producing excessive corrections.

System Planning

Designing a PHP and MySQL-based web application that functions to import sales data, process automatic calculations using the FTS–MC method, and display forecasting results along with MAPE values through a simple and easy-to-use interface. The interface design includes Login, Dashboard, Sales Data, FTS–MC Process and Results, Analysis and Forecasting, and Forecasting Results pages that display predictions for several future periods. All system functions are designed to be operated by a single actor, namely the Admin, with full access to data management and forecasting results.

System Testing

System testing was conducted using the Black Box Testing method to ensure that all functions on the web application run according to user needs without checking the program code. Testing focused on the functionality of the interface, including the authentication process, sales data management, execution of FTS-MC calculations, display of forecasting results, and navigation between pages.

System Implementation

The web-based forecasting system built using PHP and MySQL was implemented at Oyen Petshop to enable the Admin to import sales data, automatically run FTS-MC calculations, and display forecasting results along with MAPE values.

3. Results and Discussions

The monthly sales data used in this study covers 20 brands of dry cat food at Oyen Petshop during the period from April 2024 to March 2025, as shown in Table 1. The table contains product names, unit prices, and monthly sales figures, which served as the basis for selecting one brand to be analyzed further using the FTS–MC method. The Cat Choize Adult Tuna brand was chosen as the main object because it showed a relatively stable and representative sales pattern compared to other brands, with sales ranging from 156 to 326 units.

Table 1. 10 Examples of data from 20 data samples

No	Product Name	Price	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24	Jan-25	Feb-25	Mar-25
1	Cat Choize Adult Tuna	20000	174	156	192	200	204	186	184	202	258	326	238	199
2	Choize Kitten Tuna Cat Food	25,000	98	114	91	106	121	136	148	131	159	173	168	111
3	Choize Kitten Salmon Cat Food	25000	80	96	73	88	103	118	130	113	141	155	148	93
4	Chester Tuna Flavor	18,000	62	83	75	78	103	109	98	125	116	90	72	88
5	Bolt Adult Tuna	20000	164	146	182	190	194	176	174	192	248	316	228	189
6	Ori Cat Adult Tuna	20,000	124	91	102	120	109	106	101	88	117	107	178	170
7	Ori Cat Kitten Salmon	22000	169	136	147	165	154	151	146	133	162	152	223	215
8	Markotop Adult Tuna	20000	66	78	82	105	92	70	89	118	95	63	80	110
9	Maxi	33000	29	15	18	33	47	51	36	28	44	34	105	97
10	Excel Adult Tuna	13000	74	80	95	102	87	113	98	105	110	93	67	84

The results of the Fuzzy Time Series-Markov Chain (FTS-MC) calculation for the Cat Choize Adult Tuna brand show that from 12 monthly sales data, the minimum value obtained is $D_{\min} = 156$, the maximum value is $D_{\max} = 326$, and the margin parameter is $D_1 = D_2 = 2$. Using the universal set equation $U = [D_{\min} - D_1, D_{\max} + D_2]$, we obtain $U = [154,328]$. The number of intervals is calculated using Sturges' formula $n = 1 + 3{,}322 \log N$, with $N = 12$, resulting in $n \approx 4{,}584$, which is rounded to 5 intervals. The interval length is obtained from $= \frac{(D_{\max}+D_2)-(D_{\min}-D_1)}{n} = \frac{328-154}{5} = 34{,}8$. Based on these results, the population is divided into five linguistic intervals with midpoints as shown in Table 2.

Table 2. Linguistic intervals and midpoints for cat choize adult tuna

Interval	Lower Bound	Upper Bound	Midpoint ((m_i))
(u_1)	154	188.8	171.4
(u_2)	188.8	223.6	206.2
(u_3)	223.6	258.4	241.0
(u_4)	258.4	293.2	275.8
(u_5)	293.2	328.0	310.6

Based on the intervals in Table 2 and the triangular membership function defined in the methods section, five fuzzy sets are obtained, A_1 through A_5, with the following membership patterns: A_1 has full membership in u_1 and partial membership in u_2; A_2 has partial membership in u_1, full membership in u_2, and partial membership in u_3; A_3 has partial membership in u_2, full membership in u_3, and partial membership in u_4; A_4 has partial membership in u_3, full membership in u_4, and partial membership in u_5; while A_5 has partial membership in u_4 and full membership in u_5. The results of mapping the sales values of Cat Choize Adult Tuna to the main fuzzy states are presented in Table 3, where the data 174, 156, 186, and 184 are mapped as A_1; the data 192, 200, 204, 202, and 199 as A_2; the data 258 and 238 as A_3; and the data 326 as A_5. The fuzzy state series in Table 3 are then linked between consecutive periods to form the Fuzzy Logical Relationship (FLR). The FLR results are presented in Table 4, which lists the state pairs from each current state to its corresponding next state for the period April 2024-March 2025.

Table 3. Fuzzification + FLR for cat choize adult tuna

Period	Sales Volume	Fuzzy State	Next Period	FLR (Current → Next State)
April 2024	174	A_1	May 2024	$A_1 \to A_1$
May 2024	156	A_1	June 2024	$A_1 \to A_2$
June 2024	192	A_2	July 2024	$A_2 \to A_2$
July 2024	200	A_2	August 2024	$A_2 \to A_2$
August 2024	204	A_2	September 2024	$A_2 \to A_1$
September 2024	186	A_1	October 2024	$A_1 \to A_1$
October 2024	184	A_1	November 2024	$A_1 \to A_2$
November 2024	202	A_2	December 2024	$A_2 \to A_3$
December 2024	258	A_3	January 2025	$A_3 \to A_5$
January 2025	326	A_5	February 2025	$A_5 \to A_3$
February 2025	238	A_3	March 2025	$A_3 \to A_2$
March 2025	199	A_2	–	–

From these FLRs, a Fuzzy Logical Relationship Group (FLRG) is constructed by grouping all next states that originate from the same current state, as shown in Table 4. For A_1, the next states that appear are A_1, A_2, A_1, and A_2, meaning A_1 is followed twice by A_1 and twice by A_2; for A_2, the next states are A_2, A_2, A_1, and A_3; for A_3, the next states are A_5 and A_2; A_4 does not appear in the series and therefore has no FLRG; while A_5 is followed once by A_3. The frequency of transitions from each current state to the next state in Table 4 is used to construct a Markov transition probability matrix using the formula $P_{ij} = \frac{H_{ij}}{H_i}$, where H_{ij} is the number of transitions from A_i to A_j, and H_i is the total number of transitions from A_i. The results show that when the data are in state A_1, the probabilities of remaining in A_1 and moving to A_2 are equal at 0.50. In state A_2, the highest probability is to remain in A_2 with a value of 0.50, while the probabilities of moving down to A_1 and up to A_3 are 0.25 each. State A_3 has balanced probabilities of moving down to A_2 and up to A_5, both equal to 0.50; state A_4 has no transitions; while state A_5 is always followed by A_3.

Table 4. Fuzzy logical relationship group (FLRG)

Current state	$(\mathbf{A_1})$	$(\mathbf{A_2})$	$(\mathbf{A_3})$	$(\mathbf{A_4})$	$(\mathbf{A_5})$
Next state (order of occurrence)	(A_1, A_2, A_1, A_2)	(A_2, A_2, A_1, A_3)	(A_5, A_2)	-	(A_3)

Using the transition probability matrix in Table 5 and the midpoint of the interval in Table 2, initial forecasting calculations were performed for $F(t)$according to the one-to-many and one-to-one formulations described in the methods section. Forecasting began in May 2024 because the forecast value for April 2024 could not yet be calculated (initial period). The complete results of the initial forecast are shown in Table 5. The values of $F(t)$range from 181.10 to 258.40, with a pattern that follows the fluctuations of the fuzzy state and Markov transition probabilities. The final prediction$F'(t)$ is obtained by adding the adjustment valueD_t to the initial prediction (t) , where D_t is set as a multiple of half the length of the interval $\frac{l}{2} = 17.4$ based on the pattern of fuzzy state transitions between periods. The value D_t is 0 for stable transitions (same state), ± 17.4 for transitions up or down one state, and ± 34.8 for transitions of two states. The complete final forecast results, rounded to integers, are shown in Table 5.

Table 5. Initial forecast and final forecast for cat choize adult tuna

Period	Actual data $\boldsymbol{Y(t)}$	$\boldsymbol{F(t)}$	$\boldsymbol{D_t}$	Final Forecast $\boldsymbol{F'(t)}$
April 2024	174	–	–	–
May 2024	156	190.10	0	190
June 2024	192	181.10	17.4	199
July 2024	200	199.10	0	199
August 2024	204	203.10	0	203
September 2024	186	205.10	−17.4	188
October 2024	184	196.10	0	196
November 2024	202	195.10	17.4	213
December 2024	258	204.10	17.4	222
January 2025	326	258.40	34.8	293
February 2025	238	241.00	−34.8	206
March 2025	199	258.40	−17.4	241

The performance of the FTS–MC model was evaluated using MAPE with the formula $\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n} \left| \frac{Y_t - F'_t}{Y_t} \right| \times 100\%$, where $Y_t$is the actual data and F'_t is the final forecast. The calculation was performed for 11 periods (May 2024-March 2025), as shown in Table 6. The total value of $\left| \frac{Y_t - F'_t}{Y_t} \right|$is 0.9811, resulting in $\text{MAPE} = \frac{0.9811}{11} \times 100\% \approx 8.92\%$.

Table 6. MAPE calculation for cat choize adult tuna

No	1	2	3	4	5	6	7	8	9	10	11
Actual Data Y(t)	156	192	200	204	186	184	202	258	326	238	199
Forecast F(t)	190	199	199	203	188	196	213	222	293	206	241
$\boldsymbol{\frac{Y_t - F'_t}{Y_t}}$	0.2179	0.0365	0.0050	0.0049	0.0108	0.0652	0.0545	0.1395	0.1012	0.1345	0.2111

The FTS–MC model that has been constructed is then used to forecast sales of Cat Choize Adult Tuna for the next seven periods, namely April 2025 to October 2025, using the last state in March 2025 (A_2) as the starting point and applying the transition probability matrix of A_2 repeatedly. The forecasting results are shown in Table 7. The forecast values range from 224 in April 2025 and tend to decline gradually to 206 in October 2025.

Table 7. Sales forecast results for cat choize adult tuna for the period april–october 2025

	April 2025	May 2025	June 2025	July 2025	August 2025	September 2025	October 2025

Forecast F'(t)	224	215	211	208	207	207	206

Functional testing of the web-based forecasting system was conducted using the Black Box Testing approach on key features, including authentication, sales data management, FTS–MC calculation process, display of forecasting results, graph visualization, and interface navigation. A summary of the test results is shown in Table 8. All test scenarios, such as logging in with valid and invalid credentials, adding and deleting sales data, searching for data, calling the FTS–MC calculation process and displaying MAPE values, displaying a table of forecast results for the next seven periods, graphs comparing actual data and forecast results, as well as navigation and logout functions, showed that the system produced the expected output and all test cases were “Pass”.

Table 8. Black box testing results

	Features Tested	Test Scenario (Input)	Expected Results (Output)	Status
Authentication (Login)	Login Page	Enter a valid username and password.	The system successfully redirected the Admin to the Dashboard Page.	Pass
		Enter a valid username and an invalid password.	The system displays an error message and remains on the login page.	Pass
		Leaving one or both fields blank.	The system displays a validation message stating that the field is required.	Pass
Sales Data	Add Data	The administrator enters all new valid monthly sales data.	The new data has been successfully added to the database and appears in the Sales Data Table.	Pass
	Delete Data	The administrator clicks the Delete icon/button on one of the product data entries.	The system displays a delete confirmation, and after confirmation, the data is removed from the table and database.	Pass
	Data Search	The administrator enters the product name in the Search field.	The table only displays rows of data that match the search keyword.	Pass
		The administrator enters a product name that does not exist.	The table displays the message "Data not found" or an empty table.	Pass
FTS-MC Process and Results	Calculation Process	The administrator accesses the FTS-MC Process and Results page.	The system automatically displays all stages of the FTS-MC calculation (Universal Set, Interval, FLR, Transition Matrix, Initial Prediction, Final Prediction).	Pass
	MAPE Result Display	The administrator views the final calculation results on the FTS-MC Process page.	The Mean Absolute Percentage Error (MAPE) value (i.e., 8.92%) is displayed correctly according to the model calculation.	Pass
Forecast Results Display	Future Predictions	The administrator accesses the Forecasting Results page.	The system displays a table of sales forecast results ($F'(t)$) for the next 7 periods (April 2025 to October 2025).	Pass
	Visualization Graph	The administrator accesses the Analysis and Forecast page.	The comparison graph of Actual Data vs. Forecast Results and the APE (%) value graph per period are displayed correctly.	Pass
System Navigation	Navigation Menu	Click the Logout button.	The session ends and the user is redirected back to the Login Page.	Pass
		Clicking another menu link (Dashboard, Sales Data).	The user is successfully redirected to the intended page.	Pass

The implementation of the web-based sales forecasting system is demonstrated through several interface displays, such as the login page used by administrators to access the system; the dashboard page that summarizes key information such as total products, employees, and sales as well as several analysis graphs; other page presents the analysis and forecasting page with a graphical visualization comparing actual data and forecast results; Figure 2 shows the FTS–MC process page displaying the universal set, intervals, membership functions, FLR, FLRG, transition matrix, forecasting results, and MAPE values in tabular form; Figure 3 presents the analysis and forecasting page with a graphical visualization comparing actual data and forecast results; and Figure 4 shows the forecast results page displaying a table of forecast values for the next period as a basis for stock decision-making by the admin.

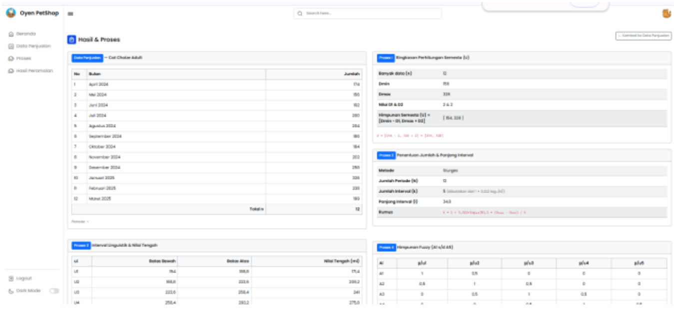
Figure 2. FTS–MC process page

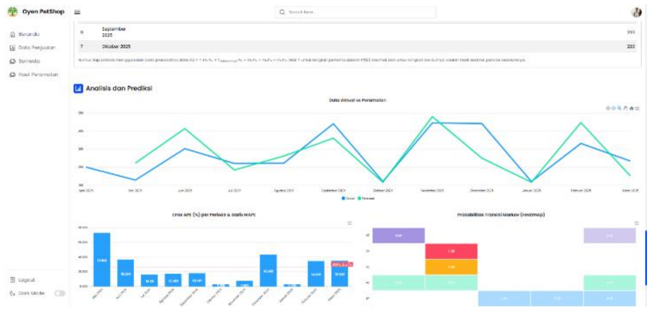
Figure 3. Analysis and forecasting page

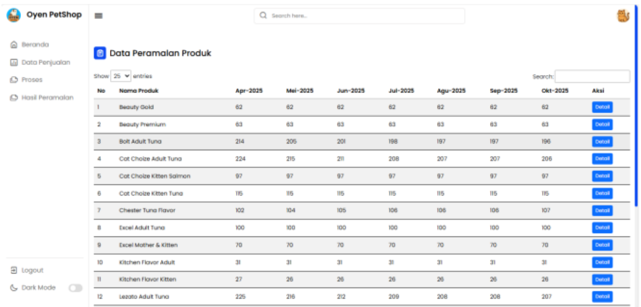
Figure 4. Forecasting results page

The final forecasting results for Cat Choize Adult Tuna $F'(t)$ in Table 6 show that the FTS–MC model is able to follow the basic pattern of sales fluctuations for Cat Choize Adult Tuna, with forecast values that are fairly close to actual data for most periods. In the early phase, the difference between actual data and forecasts is relatively small, for example in July and August 2024, where $Y(t) = 200$ and 204, while $F'(t) = 199$ and 203. Meanwhile, larger deviations appear at points of sharp change, such as December 2024 and March 2025. These larger deviations occur because both periods represent abrupt and atypical changes that are not reflected in the historical fuzzy-state transition patterns. The sharp rise in December 2024 (258) and the peak in January 2025 (326) fall outside the dominant A_1-A_2 transition tendencies learned by the model, causing the Markov transition probabilities to underestimate sudden upward movements. Likewise, the strong reversal in March 2025 generates a mismatch because the model assumes smoother transitions based on prior trends. Although these deviations indicate that the FTS-MC model is sensitive to rare extreme shifts, the overall reliability remains high, as reflected by the low MAPE value of 8.92%, showing that such errors are limited to non-representative change points. The future forecast series in Table 8 shows a relatively stable trend pattern with a slight gradual decline after the previous peak, qualitatively reflecting that demand for this product will not experience a significant surge in the future and will instead tend toward moderate and relatively constant demand conditions.

Compared to previous studies that used variations of the Fuzzy Time Series model, such as Yustin et al. (2023), which reported MAPE values of 9.904% for the Cheng model and 14.01% for the

Ruey Chyn Tsaur model, the MAPE value of 8.92% obtained in this study is below both of these values. This shows that the combination of Fuzzy Time Series and Markov Chain used in the case of cat food sales at Oyen Petshop provides competitive performance, even better than the Cheng model in the study in terms of average error value. Although differences in data characteristics and application context need to be considered, these results indicate that modeling state transition probabilities through Markov Chains contributes positively to the model's ability to capture the dynamics of fluctuating demand changes.

Thus, the practical forecast series for the next seven periods (Table 8) can be used by the owner of Oyen Petshop as a basis for planning the procurement of Cat Choize Adult Tuna stock, taking into account storage capacity, expiration dates, and working capital availability. The relatively stable forecast value in the range of 206–224 units allows for the formulation of a more measured ordering policy, for example by setting minimum and maximum order quantities that follow this trend pattern and adding a reasonable stock buffer. In addition, the web-based system that has been implemented makes it easier for business owners to update sales data and obtain forecast results automatically without manual calculations, so that decisions related to stock can be made more quickly, consistently, and based on well-documented historical data.

4. Conclusions

This study found that the Fuzzy Time Series-Markov Chain (FTS-MC) model implemented in a web-based forecasting system was able to forecast sales of Cat Choize Adult Tuna at Oyen Petshop with a MAPE of 8.92% and all application features functioned properly. This study contributes academically by demonstrating the application of FTS–MC in the context of micro businesses and packaging it in the form of an operational web system, not just a mathematical model. The main scientific contribution of this research lies in showing how fuzzy modeling and probabilistic state-transition analysis can be integrated to handle short, fluctuating sales data typically found in micro-enterprises. This integration provides an evidence-based approach for MSME forecasting that is both interpretable and operationally applicable. This system can be used by Oyen Petshop owners as a basis for more measurable stock procurement decisions and as a first step in the digitization of inventory management in MSMEs. However, this study is still limited to one store and a relatively short data period, and only uses MAPE as an evaluation indicator. Further research is recommended to expand the scope to more products and locations, use longer time series, add other evaluation metrics, and compare FTS–MC with alternative forecasting methods such as ARIMA or deep learning-based models to obtain a more comprehensive picture of performance. Future system development may also include integrating these alternative models directly into the web application to enable model benchmarking, automated model selection, and more adaptive forecasting capabilities for MSMEs.

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