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Design and Simulation of Smart Food Supply Chains for Island Regions Based on AI-LM Using Long Short-Term Memory (LSTM) Approach

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ABSTRACT

Island regions face complex challenges in ensuring sustainable food supply due to geographic isolation, limited infrastructure, and fluctuating demand–supply conditions. This study proposes the Artificial Intelligence for Logistics Management (AI-LM) framework to design and simulate smart food supply chains for archipelagic contexts, employing a Long Short-Term Memory (LSTM) approach for predictive modeling. The framework integrates multi-source data, including climate variables, commodity availability, and consumption patterns, which are processed through LSTM to forecast the Food Insecurity Composite Score (FISC) as a proxy for food security performance. Using data from North Maluku, Indonesia, the model was simulated under several scenarios to compare conventional logistics management with AI-enhanced predictive logistics. Results show that the LSTM-based model improves forecasting accuracy, reduces distribution errors, and highlights differences in model performance across provinces, with more stable predictions observed in Southeast Sulawesi and higher deviations in Papua. These findings provide a strategic roadmap for implementing AI-driven logistics systems in island regions, emphasizing their potential to enhance predictive capacity, strengthen food security, and build resilience against supply chain disruptions.

1. INTRODUCTION

Island regions face numerous challenges in food distribution due to various factors, including geographical fragmentation, poor transportation infrastructure, high operational costs, and inadequate data-based coordination among stakeholders [1]. In addition to physical and geographical challenges, they also deal with systemic barriers in institutional and coordination aspects. Food distribution in island regions involves several stakeholders, including local governments, national logistics agencies, transportation companies, and local actors, such as cooperatives and farmer groups. However, information disintegration remains widespread among these actors. The lack of an integrated, data-driven coordination system leads to slow, inefficient, and reactive decision-making. Failure to synchronize delivery schedules, demand estimates, and inventory levels can result in supply shortages, overstocking, and product waste since the goods expire before reaching consumers [2]. These difficulties are not only caused by geographical and institutional conditions, but also by environmental dynamics that introduce uncertainty.

Global climate change also increases the frequency and intensity of extreme weather phenomena in island regions, such as strong winds, heavy rain, and high waves, which directly disrupt sea and air transportation [3]. This situation results in shipping delays, increased logistics costs, and potential damage to goods, particularly perishable food commodities. In the long term, this could lead to severe food insecurity, which would be particularly detrimental to communities living on small islands that are highly dependent on external supplies.

Several previous studies have examined these challenges. Trienekens et al. [4] found that limited transparency in the food supply chain is a major obstacle that leads to distribution inefficiencies. In line with their findings, Hassini et al. [5] stated that the application of digital technology, such as blockchain and IoT sensors, can increase transparency and efficiency of food distribution. Meanwhile, Wang et.al. [6] revealed that the integration of advanced technology in food supply chain management can reduce the level of food spoilage and increase the system's responsiveness to fluctuating market demand.

In this context, the application of AI-based intelligent systems has emerged as an innovative solution to address various challenges in food distribution [7]. By applying AI technology, logistics management can produce accurate predictive analysis, optimize distribution routes, and organize adaptive delivery schedules based on weather conditions, thereby increasing transparency and coordination among stakeholders in real-time [8-10].

This research aims to design and simulate a Smart Food

Supply Chain (SFSC) model for the island region, focusing on Artificial Intelligence for Logistics Management (AI-LM). The proposed AI-LM model integrates machine learning algorithms, Internet of Things (IoT), and blockchain to generate an intelligent, adaptive, and transparent logistics ecosystem. By implementing this method, this model is expected to overcome the challenges of food distribution in island regions, increase efficiency, and significantly reduce the level of food damage.

The implication of this research is its contribution as a basis for more effective, efficient, and sustainable food logistics policies in island regions, especially in developing countries with similar geographical conditions. Furthermore, it is expected that the implementation of AI-LM will make a significant contribution to achieving food security, enhancing the quality of life in the community, and promoting environmental sustainability by reducing food waste.

This study fills a research gap by applying the AI-LM framework with Long Short-Term Memory (LSTM) in island regions, which remain largely underexplored in AI-based food logistics research. It also introduces the integration of LSTM with the n8n workflow automation platform, providing a novel methodological approach for predictive simulations and real-time monitoring in food supply chain management.

2. LITERATURE REVIEW

2.1 Food distribution challenges in island regions

Island regions are characterized by a group of small islands with limited accessibility, presenting unique logistical constraints that differ significantly from those in continental areas. Research conducted by Yudiyta et al. [11] revealed that the general characteristics of the island regions in Indonesia include limited agricultural land, high dependence on the fisheries sector, and poor food distribution infrastructure. The study used a post-positivist approach to understand the social and institutional dynamics that influence the success of policy implementation. The results showed that food security in island areas is highly vulnerable, due to not only difficulties in local production but also challenges in food distribution and accessibility between islands.

2.2 Blockchain and IoT in food distribution

Blockchain has been widely used to improve traceability and transparency in food distribution [12]. This system records every transaction and movement of goods in an immutable digital ledger, enabling rapid auditing and tracking of the source of problems. Duan et al. [13] explained that blockchain can reduce cases of food counterfeiting and increase consumer trust.

Meanwhile, the IoT plays a significant role in monitoring the physical condition of food during the distribution process [14]. IoT sensors can record temperature, humidity, and vibration data, which helps maintain food quality, especially fresh produce [15]. Complementary features between blockchain and IoT have been widely discussed in recent studies as a potential intelligent architecture for supply chains.

2.3 The concept of food supply chain and its efficiency

Food Supply Chain (FSC) is an integrated system that connects producers, distributors, and final consumers. Some common factors that greatly influence FSC efficiency are coordination, distribution speed, and adaptability to changes in demand and environmental disturbances [16]. Research conducted by Ganbold et al. [17] revealed that information technology capabilities play a significant role in driving supply chain integration (SCI), which ultimately has a positive impact on a company's operational performance. IT capability dimensions, such as cross-functional applications and supply chain applications, significantly strengthen internal and external integration. In relation to island regions, logistics efficiency requires an intelligent systems approach capable of adapting to geographic and environmental uncertainties.

2.4 The application of artificial intelligence in the food sector

Artificial intelligence (AI) offers significant potential across all aspects of the food system, including agricultural production processes, distribution management, and food waste reduction. Soori et al. [18] stated that AI is capable of learning patterns and adapting to operational changes, making it highly suitable for dynamic and complex distribution systems.

Javaid et al. [19] highlighted various AI applications in the agricultural sector, including weather prediction, crop health monitoring, and early detection of pests and diseases based on digital images. This approach aligns with the concept of precision agriculture, aiming to increase efficiency, crop yields, and environmental sustainability.

Meanwhile, Onyeaka et al. [20] discovered the roles of AI in reducing food waste and strengthening the circular economy system in the food sector. AI can accurately predict demand, optimize inventory and distribution logistics, and classify food waste for efficient reuse or distribution. Their findings suggest that integrating AI can support resource efficiency, reduce carbon emissions, and contribute to achieving global food sustainability goals.

However, most of these studies have been conducted in the context of land infrastructure or metropolitan areas with high data access and connectivity. Studies on AI in geographically remote or island regions are still very limited, and even those that exist tend to focus on weather prediction or precision agriculture, rather than food logistics.

3. METHODOLOGY

This research employed a design-based research (DBR) approach [21, 22], combined with system simulation to design and test an AI-LM model in the context of a food supply chain in island regions. The methodology aims to develop adaptive and replicable technology-based solutions while validating their effectiveness in complex and remote geographic conditions.

3.1 Research approach

This research employed a quantitative-constructivist approach, comprising two main stages:

1. AI-LM model design: involving needs mapping, identification of technology components (AI, IoT, & Blockchain), and food logistics structures in island regions.
2. Model simulation and evaluation: performed using

the n8n workflow automation platform and Google Sheets as a dynamic database to imitate real distribution conditions and measure model performance.

The LSTM model was implemented with two hidden layers (64 and 32 neurons), using *tanh* and *sigmoid* activations, and a dense output layer with linear activation. Training was performed with the Adam optimizer (learning rate = 0.001), batch size of 32, dropout rate of 0.2, and early stopping within 30–40 epochs. These specifications are provided to ensure reproducibility of the experiments.

3.2 Data collection

Data were collected through two primary sources:

1. Primary data: results of observations and structured interviews with stakeholders in the food logistics sector (distributors, the department of agriculture and Food Security, the department of fisheries and maritime affairs, and local fishermen/farmers) in island regions in North Maluku Province.
2. Secondary data: statistical reports on food security, weather data, historical demand patterns, and references from journals and official government documents related to food logistics and distribution.

Tables 1-3 present sample statistical data for the food security index (FSI), weather data, and historical food demand patterns.

Table 1. Sample data of the FSI in several island regions in Indonesia in 2024

Provinces	FSI
Bangka Belitung Islands	68.92
Bali	85.76
Southeast Sulawesi	76.22
West Nusa Tenggara	74.21
East Nusa Tenggara	65.92
Maluku	62.68
North Maluku	61.44
Papua	35.95

Table 1 shows the FSI values for several island provinces in Indonesia in 2024. Bali has the highest FSI value of 88.23, while Papua has the lowest value of 40.21. Other island provinces, such as West Nusa Tenggara (78.44), Southeast Sulawesi (76.68), and East Nusa Tenggara (70.91), have FSI values in the middle range. Meanwhile, the eastern regions of Indonesia, Maluku (62.68) and North Maluku (61.44), have relatively lower FSI values compared to other island provinces.

Table 2 shows the average rainfall and sea wave conditions in North Maluku Province in 2024. Based on rainfall data, it can be observed that the peak of the rainy season occurs in December, with rainfall reaching 540 mm, followed by June and May, which receive 360 mm and 235 mm of rainfall, respectively. This indicates that the rainy period lasts quite a long time, from October to June, with peak intensity at the end of the year. In contrast, the dry period is relatively short, specifically in February (24 mm) and March (37 mm), with very low rainfall. Meanwhile, the highest ocean waves were recorded in July, with an average of 2.8 meters, followed by June, August, and December, each with an average of 2.5 meters. This period coincides with the seasons of the east and west winds, bringing higher waves to the waters of North Maluku. On the contrary, relatively calm ocean waves occur in April (1.0 m), followed by March and May, with heights of around 1.2 m.

Table 2. Sample data of rainfall in 2024

Month	Rainfall (mm)	Average Ocean Waves (m)
January	75	2.0
February	24	2.2
March	37	1.2
April	135	1.0
May	235	1.2
June	360	2.5
July	285	2.8
August	46	2.5
September	225	1.5
October	240	1.2
November	195	2.0
December	540	2.5

Table 3. Sample data of historical food demand patterns

Commodity	Average Monthly Demand (ton/month)	Demand Spike (tons/month)	Peak Demand
Rice	95	130	Ramadan and Eid al-Fitr (April–May)
Egg	20	40	Ramadan, Christmas, New Year
Fresh vegetable	85	35	Stable demand throughout the year
Fresh fish	30	100	Post-harvest (Feb.–Mar., Aug.–Sep.)

Table 3 presents the historical food demand patterns in North Maluku based on the main commodity types. Based on the table, it can be seen that the average monthly demand for rice is 95 tons, but it can jump to 130 tons, especially during the Ramadan and Eid al-Fitr periods (April–May). This reveals a strong correlation between rice consumption and religious occasions, especially when public demand increases significantly. The average monthly demand for eggs is approximately 20 tons, with spikes in demand reaching 40 tons. Typically, this increase occurs around major religious holidays, such as Ramadan, Christmas, and New Year's Day, when consumption of egg-based foods increases significantly. Meanwhile, the average monthly demand for fresh vegetables is relatively high, at 85 tons. Vegetable demand remains relatively stable throughout the year, with spikes of around 35 tons. This indicates that daily household needs remain constant regardless of the season or holidays. Fresh fish, North Maluku's leading commodity, exhibits a different pattern. The average monthly demand is approximately 30 tons per year, but it can spike to 100 tons during the post-harvest periods, particularly in February–March and August–September. This indicates that the availability and price of fresh fish are highly dependent on the fishing season, which in turn influences people's consumption patterns.

Figure 1 below illustrates the overall research stages.

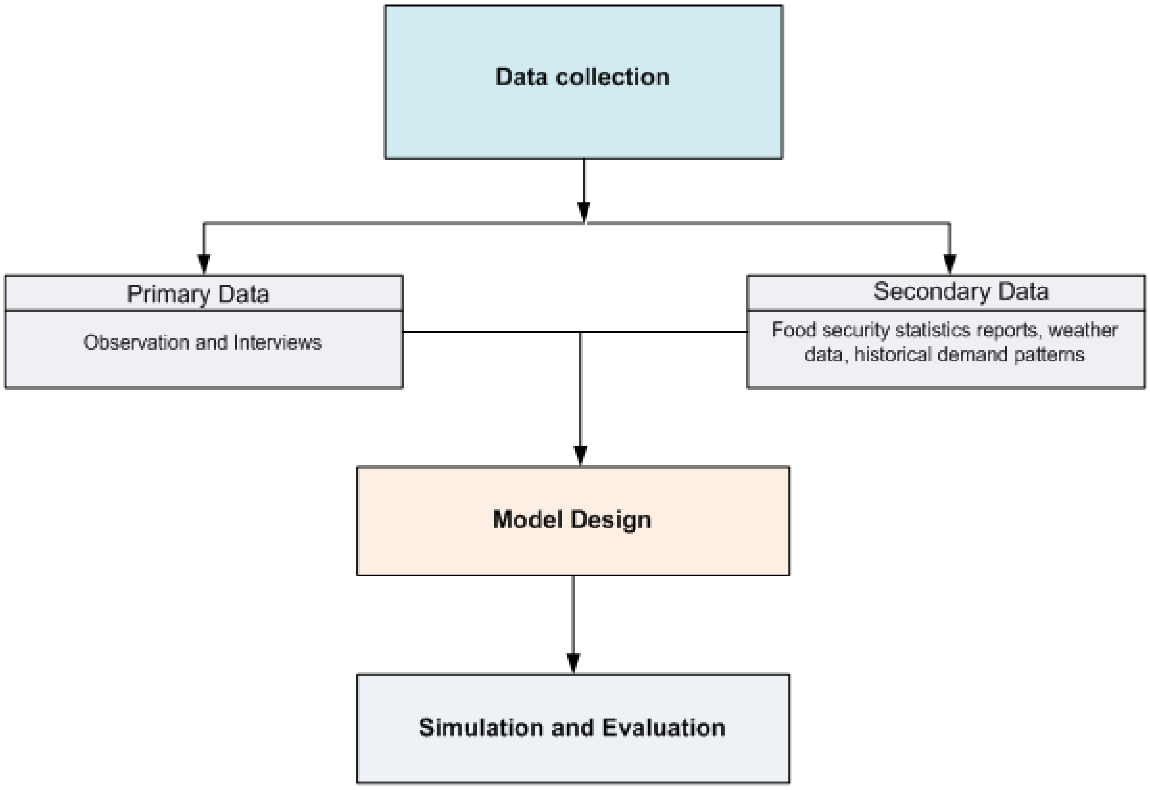

Figure 1. Research stages

4. RESULTS AND DISCUSSION

This section presents the design results of the AI-LM system, utilizing the LSTM approach, with a focus on the technical aspects of implementation. The design process involved developing a model architecture that integrated historical food demand data, the FSI, and environmental variables, including rainfall and ocean waves. The data were processed through an LSTM network to generate predictions of food demand and distribution in the island regions.

In addition to LSTM modeling, the system design was also equipped with a workflow automation scheme using n8n as a dynamic logistics distribution simulation framework. This stage demonstrated how data flows, from input to preprocessing, modeling, and prediction output, were integrated into a system architecture that can be tested and further developed.

4.1 AI-LM architecture design

The AI-LM system architecture was designed to handle the complexity of food distribution in island regions by utilizing dynamic multi-source data.

This design consisted of three main layers: a data input layer, an LSTM modeling layer, and an n8n workflow integration layer, which are described below.

1. Data Input Layer

The data consisted of:

FSI for each island province.

Historical data on rainfall and ocean wave height.

Data on demand for basic food (rice, eggs, vegetables, and fresh fish).

The data were then formatted into a time series to suit the needs of LSTM predictive modeling.

2. LSTM Modeling Layer

The LSTM network was chosen due to its ability to overcome the problem of vanishing gradients in long sequential data.

The architecture consisted of an input layer (multivariate time series), several hidden LSTM layers with tanh and sigmoid activation functions, and a dense layer to generate food demand prediction values.

This model was trained using historical data to predict demand patterns based on weather factors, ocean conditions, and consumption trends.

3. Workflow Integration Layer (n8n)

The prediction results from LSTM were integrated with the n8n automation workflow.

The n8n managed the data flow from the input source (Google Sheets/statistics) to the prediction module, and then linked the output to the monitoring dashboard.

Through this integration, the system can provide dynamic notifications regarding potential spikes in demand and distribution risks due to weather/ocean disruptions.

Figure 2 shows the results of the AI-LM architecture design.

4.2 n8n workflow design

The n8n workflow design for the AI-LM model focused on integrating input data, predictive processing with LSTM, and output distribution in the form of notifications and interactive dashboards. This modular workflow was easily expandable to meet the needs of the food supply chain in the island regions.

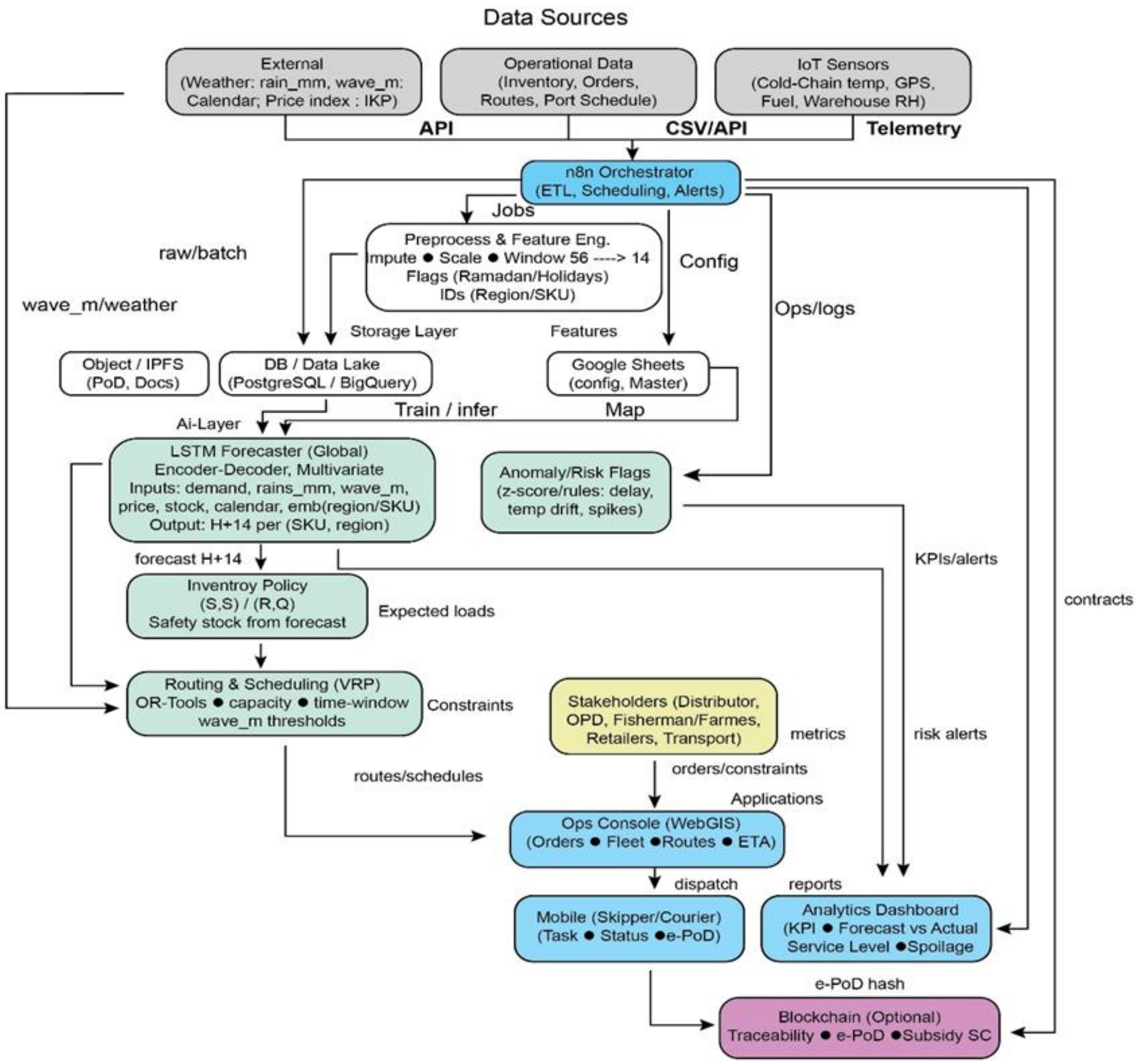

Figure 2. The AI-LM architecture design

1. Node Input (Ingest)
   - Connecting external data sources: Google Sheets, weather APIs (rainfall, wind, waves), and historical demand databases.
   - Automatic triggers use Cron Scheduler, so the dataset is updated periodically without manual intervention (e.g., every 1–3 hours).
2. Node Pre-processing
   - Cleaning (missing/outliers), scale normalization, category encoding, and time-series transformation (windowing/lag/rolling).
   - Unifying heterogeneous data—rainfall, wave height, demand volume—into a uniform feature scheme for LSTM input.
3. Processing Node (LSTM)
   - Executing a Python script or containerized application to perform time-series-based demand prediction using an LSTM model.
   - Considering climate factors and seasonal patterns. Output: Estimated demand volume and alert threshold.
4. Output Distribution Node
   - Saving results to Google Sheets/DB (historical log), displaying on dashboard, and sending automatic notifications (Email/Telegram bot) to stakeholders (distributors, department of agriculture/maritime, fishermen/farmers).
5. Monitoring & Evaluation Node
   - Performance validation: compare predictions vs realizations (accuracy, MAE/RMSE, MAPE).
   - Feedback loop for hyperparameter/feature updates when deviation increases to allow the model to adapt to geographic and consumption dynamics.

Figure 3 shows the n8n workflow design.

Next, Figure 4 presents the step-by-step flow of the process carried out on n8n.

The following is a detailed explanation of the process flow diagram of n8n:

1. Start / Trigger Workflow
   - The workflow starts when the Execute Workflow button is pressed.
   - This serves as the initial trigger for running the entire series of nodes.

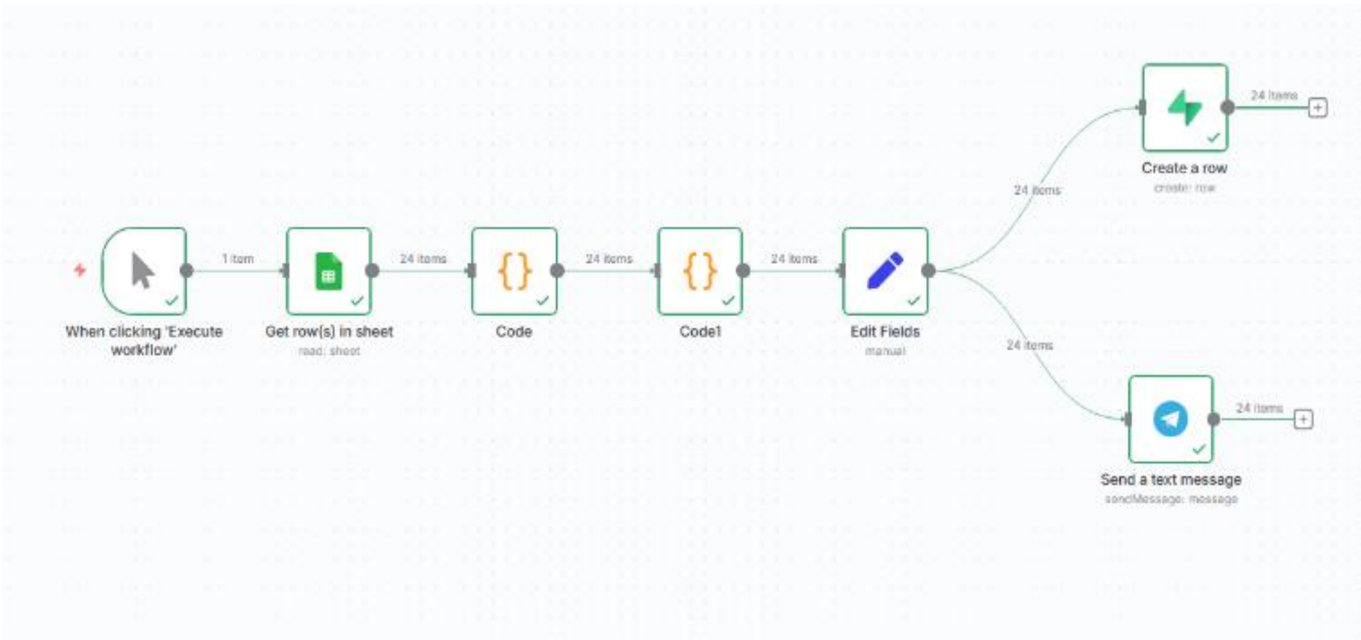

Figure 3. The n8n workflow design

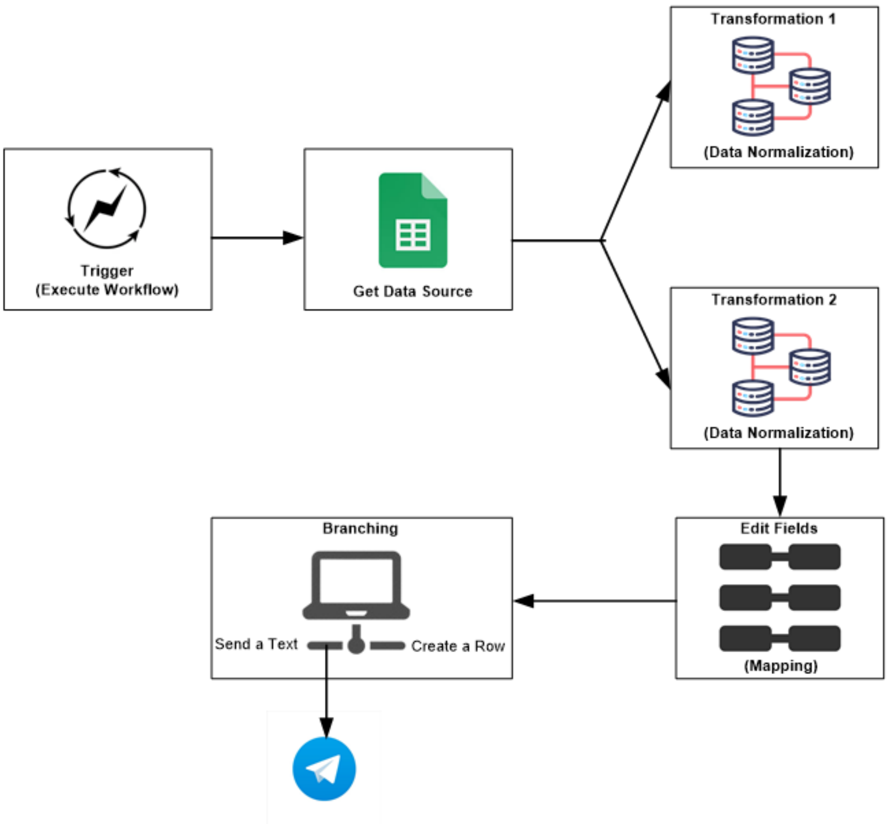

Figure 4. The n8n flowchart

2. Get Row(s) in Sheet
   - This node retrieves row data from a specified Google Sheet.
   - The retrieved data is usually raw input (e.g., transaction data, logistics requests, or respondent information).
3. Code (Data Transformation 1)
   - Data from the Google Sheet is processed using a script (JavaScript/Function Node) T.
   - his stage is typically used to perform initial transformations, such as parsing text, filtering specific rows, or simple calculations.
4. Code (Data Transformation 2)
   - The data is processed again in the second code node.
   - This stage is typically used for data cleaning and formatting, such as ensuring correct date formats, removing blank values, or standardizing variables.
5. Edit Fields (Mapping)

- This node restructures the data to suit the output requirements.
- For example, renaming fields, adding new columns, or adjusting the JSON structure for ease of use in subsequent steps.

6. Branching (Flow Branching)
   - From here, the flow branches into two parallel outputs:
   - Create a Row: Saves the processed data to a Google Sheet or other database.
   - Send a Text Message: Sends a notification (e.g., WhatsApp, Telegram, or SMS) based on the newly entered data.

4.3 Simulation and testing

The simulation and testing procedures were carried out by building an LSTM-based workflow involving several stages. First, the quality of multi-source data, such as Google Sheets, weather APIs, and historical databases, was preprocessed through several stages, including normalization, cleaning, and the formation of time windows (sequences) as model input. Next, the LSTM model was trained on the training data using an early stopping mechanism to prevent overfitting, and data validation was employed to assess the model's performance. The evaluation was conducted using accuracy metrics, including MSE, MAE, RMSE, and MAPE, to compare actual and predicted values. Furthermore, performance testing was performed by recording the average training time per epoch, inference time per sample, and processing throughput. Table 4 shows the results of the comparison between the actual values (FISC Actual) and predicted values (FISC Predicted) from the LSTM model in several provinces and certain months, and calculates the Absolute Error as the absolute difference between the two values.

The LSTM model's prediction results demonstrate clear differences in accuracy between provinces as well as seasonal variations. In Papua, the actual FISC values exhibit distinct seasonal spikes, particularly in April–May (Ramadan and Idul Fitri), July (Idul Adha), and December (Christmas and New Year). For instance, the FISC Actual rose to 42.0 in April and 45.0 in May, while the predicted values remained lower at 53.30 and 51.50, producing errors of 11.58 and 6.3, respectively. Similarly, in December, the actual FISC increased sharply to 48.0, but the prediction dropped to 35.51, generating an error of 8.5. These deviations suggest that the model cannot yet adequately capture sudden surges linked to religious and cultural events, which are typically accompanied by rising household demand and supply chain disruptions.

In contrast, Southeast Sulawesi presents a more stable seasonal pattern. Actual FISC values show moderate increases during Ramadan–Idul Fitri, Idul Adha, and year-end holidays, while the LSTM model demonstrates better adaptability in this region. The prediction error declined from 15.38 in January to just 3.1 in June, and although fluctuations remain (e.g., May with an error of 13.3), the model generally follows the observed trend more closely.

These findings indicate that LSTM models are relatively more capable of learning patterns in areas with more stable data conditions [23, 24]. In areas with extreme conditions, longer historical data and additional features are required for more accurate predictions.

Table 5 shows a summary of the LSTM model evaluation results.

Table 4. Comparison of actual results (FISC Actual) and predicted values (FISC Predicted)

Province	Month	FISC Actual	FISC Predicted	Absolute_Error
Papua	January	36.0	62.85	26.8
Papua	February	36.0	60.18	24.18
Papua	March	36.0	55.58	15.58
Papua	April	42.0	53.30	11.58
Papua	May	45.0	51.50	6.3
Papua	June	37.0	51.30	12.0
Papua	July	41.0	46.80	5.8
Papua	August	36.0	44.55	8.4
Papua	September	36.0	42.30	6.3
Papua	October	36.0	40.10	4.0
Papua	November	43.0	37.80	5.2
Papua	December	48.0	35.51	8.5
Southeast Sulawesi	January	76.19	60.81	15.38
Southeast Sulawesi	February	76.19	63.99	12.20
Southeast Sulawesi	March	76.19	67.28	8.91
Southeast Sulawesi	April	82.11	69.52	12.5
Southeast Sulawesi	May	85.05	71.70	13.3
Southeast Sulawesi	June	77.10	73.90	3.1
Southeast Sulawesi	July	81.15	76.15	4.9
Southeast Sulawesi	August	76.35	78.33	2.3
Southeast Sulawesi	September	76.15	80.55	4.5
Southeast Sulawesi	October	76.15	82.77	6.7
Southeast Sulawesi	November	83.10	84.91	1.9
Southeast Sulawesi	December	85.66	87.10	2.1

Table 5. Summary of LSTM model evaluation results

Dataset	MSE	MAE	RMSE	MAPE %
Train	60.769	6.928	7.795	9.534
Validation	185.334	13.437	13.613	29.07

In Table 5, the evaluation results demonstrate that the LSTM model achieves satisfactory performance on the training dataset, with relatively low errors (MSE = 60.77; MAE = 6.93; RMSE = 7.80; MAPE = 9.53%). This suggests that the model is able to effectively capture temporal dependencies within the training period. However, when applied to the validation dataset, the errors increase substantially (MSE = 185.33; MAE = 13.44; RMSE = 13.61; MAPE = 29.07%), indicating a marked decline in predictive accuracy on unseen data. This discrepancy shows that, although the use of a 12-month dataset improves learning compared to shorter horizons, the model still struggles with generalization. The limitations are likely related to the relatively short one-year observation window, which does not fully capture inter-annual seasonal variations, and the inherent complexity of the LSTM architecture. Future research should therefore focus on extending the dataset to cover multiple years, introducing regularization methods (such as Dropout and L2 regularization), and employing province-specific modeling to better capture localized dynamics. Figure 5 presents the training history curve of the LSTM model for predicting FISC (FSI).

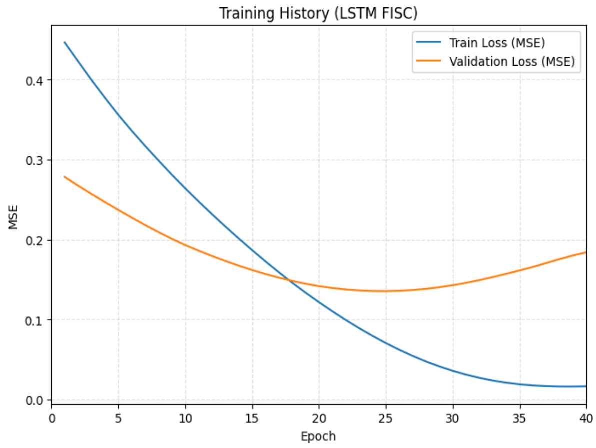

Figure 5. Training history curve of the LSTM model for predicting FISC (FSI)

4.4 Discussion

Simulation results indicate that the LSTM model is capable of accurately learning patterns in the training data. This is reflected in the Mean Squared Error (MSE) value of 0.0339 and Mean Absolute Error (MAE) of 0.1272 on the training dataset. This low error value indicates that the model successfully adapted to the characteristics of the training data. However, on the validation dataset, model performance decreases significantly, with an MSE value of 286.80 and an MAE of 16.05. A significant difference between the results on training and validation data indicates overfitting, where the model effectively memorizes patterns in the training data but struggles to generalize to new data [25].

This is a common phenomenon in the application of deep learning-based models, especially on datasets with a limited size. LSTM, as a variant of the Recurrent Neural Network (RNN), has a complex structure with a relatively large number of parameters, so it requires a sufficient amount of historical data to achieve optimal generalization ability [26]. In this study, only three months of data (January–March) were available for each province, which limited the model's temporal variation. Consequently, the model was unable to capture seasonal patterns and long-term fluctuations, which are necessary for food security analysis.

Furthermore, the prediction results showed variations in accuracy across provinces. In Papua, the model produced predictions significantly higher than the actual values, with an absolute error of 15–24 points. Papua has extreme conditions, such as high rainfall and ocean waves, which are very different from those in other provinces. In contrast to Southeast Sulawesi, the model showed more stable performance, with the error decreasing from 15.38 in January to 8.91 in March. These findings indicate that the model can learn patterns more easily in areas with stable conditions. Meanwhile, in areas with extreme conditions, additional data and more adaptive modeling techniques are required.

The training history graph also aligns with these findings. The training loss value decreases significantly until it stabilizes at a low level. Meanwhile, the validation loss decreases but plateaus at a higher level and remains constant after the 20th epoch. This pattern confirms the indication of overfitting, where the model focuses too much on the training data and fails to improve accuracy on the validation data. There are several strategies to overcome this problem, such as extending the historical data horizon (at least 12–24 months), adding exogenous features like food prices and logistics indicators, using regularization techniques like dropout, and applying evaluation methods that are more suitable for time series data, for example, walk-forward validation [27].

The LSTM model in this study demonstrates excellent performance on the training data but does not perform optimally on the validation data. This indicates the need for improvement strategies in terms of data quality and quantity, as well as model design. By incorporating historical data and adapting the architecture, LSTM is expected to deliver more accurate and reliable predictions, thereby supporting food security analysis in island regions.

5. CONCLUSIONS

This study demonstrated that the design and simulation of an AI-LM-based Smart Food Supply Chain using the LSTM approach can provide an initial overview of the potential role of deep learning in supporting food security in island regions. While the LSTM model adapts well to training data, its limited generalization highlights the constraints posed by scarce historical data and high inter-provincial heterogeneity conditions that call for per-province modeling or spatial embedding to improve forecasting accuracy.

The main contribution of this research lies in integrating an AI-LM-based workflow for real-time prediction of the FSI, offering both methodological insights and a practical foundation for developing adaptive, data-driven supply chain systems tailored to island contexts. Future improvements should include expanding historical datasets, incorporating exogenous variables such as food prices, logistics costs, and policy changes, and exploring hybrid architectures to mitigate overfitting.

In practice, challenges remain in terms of data acquisition, infrastructure limitations, and human resource readiness. These can be addressed through standardized data collection frameworks, cloud and edge computing solutions, and institutional partnerships to ensure sustainable deployment. Overall, despite existing limitations, the findings confirm the feasibility of AI-LM-based LSTM models as a foundation for more accurate, adaptive, and sustainable smart food supply chains in island regions.

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NOMENCLATURE

B	dimensionless heat source length
CP	specific heat, J. kg^{-1}. K^{-1}
g	gravitational acceleration, m.s^{-2}
k	thermal conductivity, W.m^{-1}. K^{-1}
Nu	local Nusselt number along the heat source

Greek symbols

α	thermal diffusivity, m^2. s^{-1}
β	thermal expansion coefficient, K^{-1}
ϕ	solid volume fraction
Θ	dimensionless temperature
μ	dynamic viscosity, kg. m^{-1}.s^{-1}

Subscripts

p	Nanoparticle
f	fluid (pure water)
nf	nanofluid