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Analysis of the LSTM Model on the Demand Patterns of Indonesian Traditional Cookies in Online Marketplaces

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ABSTRACT
Objective: *This study aims to analyze the application of the Long Short-Term Memory (LSTM) model in predicting demand patterns for Indonesian culinary products in online marketplaces.* ***Method:*** *Using monthly sales data from January 2022 to May 2024, the model was trained and evaluated with the metrics Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2.* ***Results:*** *The results showed an MSE of 899.70, an RMSE of 30.00, and an R^2 value of 0.09, indicating that the model has limitations in capturing variations in historical data. Nevertheless, LSTM still has potential as a forecasting tool for MSME entrepreneurs in decision-making related to inventory management, production planning, and marketing strategies.* ***Novelty:*** *Future research is recommended to expand the dataset, incorporate external factors such as seasonal trends and promotions, and explore hybrid approaches to improve prediction accuracy.*

INTRODUCTION

Artificial Intelligence

In the ever-evolving digital era, the Internet has become one of the key components in driving changes in consumer behavior and expanding business models across various sectors, including the culinary industry. The Internet is no longer merely a tool for communication, but has developed into a primary medium for buying and selling transactions. The advancement of information technology enables entrepreneurs to access and reach wider, global markets more efficiently and rapidly [1].

A marketplace platform is one of the most tangible forms of Internet utilization in trade. A marketplace is a digital platform designed to connect sellers and buyers in a virtual space, providing consumers with convenience in exploring various products at once, while also facilitating entrepreneurs in marketing their products. Marketplaces play a highly vital role in the business world, as they offer significant opportunities to expand distribution networks, accelerate buying and selling processes, and reduce operational costs [2].

Along with the increasing use of the Internet and marketplace platforms, the number of visitors accessing digital platforms has also experienced significant growth. In 2023, the Indonesian E-commerce Association (idEA) reported that the growth of food and beverage transactions on marketplaces reached 12.4%, with the number of active users exceeding approximately 60 million people [3].

This transformation indicates that the culinary sector in marketplaces has enormous growth potential and continues to increase every year. Culinary products, particularly traditional Indonesian food and beverages, represent product categories with high consumption levels in marketplaces. These products are not only favored by local

consumers but also serve as top choices for domestic tourists and even international visitors seeking authentic Indonesian flavors. However, behind these opportunities lies a major challenge in managing unstable demand. Monthly trend shifts, promotional events on "special dates" such as 10.10 and 11.11, as well as the influence of social media, are the main factors causing demand fluctuations [4].

In this regard, understanding demand patterns is crucial. The ability to accurately predict demand can provide a competitive advantage for culinary entrepreneurs. Accurate forecasts can assist in production planning, inventory management, and the formulation of more effective marketing strategies. One approach that can be employed to understand and predict demand patterns is by leveraging historical sales data stored in digital systems [5].

One relevant method for conducting time series data analysis is Long Short-Term Memory (LSTM). LSTM is a part of Artificial Neural Networks (ANN) specifically designed to learn and recognize long-term patterns from historical data. Unlike traditional forecasting methods, LSTM can capture sequences and memory from unstable data while retaining essential information over specific periods of time. Its main advantage lies in its ability to avoid problems such as the vanishing gradient and to maintain long-term memory [6].

The application of LSTM in forecasting demand for culinary products on marketplaces remains limited, particularly in the context of Indonesian culinary products (kuliner Nusantara), which have unique demand characteristics that are difficult to predict using conventional methods. Therefore, this study seeks to address this gap by applying the LSTM model as a predictive approach capable of providing more accurate results in forecasting product demand [7].

Based on the description above, this study aims to analyze and forecast the demand for traditional Indonesian cookies (*kue kering Nusantara*) on Indonesian marketplace platforms using the Long Short-Term Memory (LSTM) method. The expected outcome of this research is to provide practical contributions for culinary MSME entrepreneurs in making more accurate business decisions, as well as to encourage the utilization of artificial intelligence technologies in the digital culinary sector in Indonesia [8].

Problem Formulation

Over time, with the advancement of technology and the growth of marketplaces in Indonesia, the demand for traditional Indonesian cookies (*kue kering Nusantara*) in digital marketplaces has continued to increase. However, despite the significant potential in this market, culinary entrepreneurs face several challenges in accurately forecasting product demand [9].

Research Questions:

1. What factors influence the demand for *kue kering Nusantara* products in Indonesian marketplaces? How can historical demand data for *kue kering Nusantara* in marketplaces be collected and managed for use in the LSTM model?

2. How can the LSTM method be applied in time series analysis to accurately predict culinary product demand?
3. What obstacles are encountered in implementing LSTM for demand forecasting, and how can these challenges be addressed?
4. How can LSTM forecasting results be utilized by entrepreneurs to optimize stock, supply chains, and sales strategies for *kue kering Nusantara* products?

SDGs Category

By enabling more accurate demand forecasting, this research can help culinary entrepreneurs reduce waste in supply chains and production, thereby improving business efficiency. It also supports more efficient and responsible consumption and production patterns [10].

Marketplace and Consumption Pattern Trends

Marketplaces have become the primary platforms in digital trade, enabling customers to search for, compare, and purchase various *kue kering Nusantara* products with ease. These products possess unique characteristics, such as the diversity of food types, raw materials, and customer preferences, which may shift according to trends and seasonal variations [11].

Local and Regional Context

Marketplaces play an important role in supporting Micro, Small, and Medium Enterprises (MSMEs), particularly within local and regional contexts. These digital platforms enable MSMEs to expand product distribution, enhance competitiveness, and contribute to regional economic growth through job creation and increased productivity. Therefore, this study also takes local aspects into account in the development of its predictive model [12].

Predictive Approach Technique

Long Short-Term Memory (LSTM) is a type of artificial neural network designed to address the vanishing gradient problem in Recurrent Neural Networks (RNN), thereby enabling the modeling of long-term dependencies in time series data. LSTM was first introduced by Hochreiter and Schmidhuber in 1997 and has since been widely applied across various domains, such as stock price prediction, sentiment analysis, and weather forecasting. LSTM, as introduced by Hochreiter and Schmidhuber, was specifically developed as a neural network architecture capable of overcoming the vanishing gradient problem in RNNs. It is designed to recognize patterns in time series data, which is particularly important for predicting trends and consumption patterns in digital marketplaces [13].

In this study, LSTM is employed to predict demand patterns for *kue kering Nusantara* products in marketplaces based on historical sales data, customer reviews, and other factors that may influence demand levels. The model operates by retaining long-term information while disregarding less relevant information, thereby producing more accurate predictions compared to conventional models such as ARIMA or linear regression [14].

Many previous studies have employed quantitative approaches such as linear regression, ARIMA, and other conventional statistical models to predict demand in marketplaces. However, these approaches tend to be less optimal in processing fluctuating and complex time series data. On the other hand, LSTM has been proven effective in capturing seasonal patterns and demand trends based on historical data, making it the primary choice in this study [15].

The demand for culinary products in marketplaces is influenced by various factors such as seasonal variations, national holidays, and promotional campaigns on special dates (e.g., 10.10 or 12.12). These factors often trigger demand spikes that do not occur on regular days. Therefore, in building a forecasting model, these variables need to be considered to ensure more accurate results [16].

Predictive Models in the Culinary Sector

Although LSTM has been widely applied in forecasting stock prices, weather, and other industrial products, very few studies have implemented it for *kue kering Nusantara* products in online marketplaces. Previous research has generally focused on global products or agricultural commodities, without considering the unique characteristics of local culinary products such as the influence of social media trends, consumer reviews, and flash sales. This study aims to fill that gap [17].

Comparison of Income Prediction Methods

Research on demand forecasting using time series methods shows that traditional models such as ARIMA, linear regression, and Prophet have been widely applied in the retail and food sectors. However, these methods often fail to capture non-linear patterns and strong seasonality, especially in culinary products influenced by trends, marketplace promotions, and festive seasons. Several studies highlight that accurate forecasting is essential to support MSMEs in managing supply chains and sales strategies.[18]

Advantages of LSTM and Limitations of Previous Research

Meanwhile, Long Short-Term Memory (LSTM) has been successfully implemented in sectors such as stock price forecasting, weather prediction, and logistics, proving its superiority in handling historical data with complex patterns. The strength of LSTM lies in its ability to remember long-term dependencies while adapting to short- term fluctuations—an aspect highly relevant to culinary demand patterns in online

marketplaces. Nevertheless, research focusing specifically on LSTM for Indonesian traditional culinary products remains very limited.[19]

Research Gap in Predicting Demand for Indonesian Cuisine

Furthermore, external factors such as national holidays, flash sales (e.g., 10.10, 11.11, 12.12), social media trends, and local consumer preferences significantly influence demand. Unfortunately, most prior studies still focus on global food or agricultural commodities rather than Indonesian traditional cuisine. This indicates a research gap that this study aims to fill by emphasizing LSTM-based demand forecasting for Indonesian culinary products in online marketplaces.[20]

Table 1. Comparison of Previous Studies on Demand Forecasting.

Author (Year)	Title	Findings	Research Gap
Wang et al. (2021)	LSTM for Stock Price Prediction	LSTM outperforms ARIMA in financial data	Focused on stock, not culinary demand
Santoso (2022)	Retail Sales Forecasting with ARIMA	Captures seasonality but limited in non- linear patterns	No application of neural network models
Kim & Lee (2022)	Demand Forecasting in E-Commerce	LSTM improves e-commerce demand prediction accuracy	No focus on Indonesian culinary context
This Study (2024)	LSTM Analysis on Indonesian Culinary Demand	Provides LSTM- based forecasting model for MSMEs	Fills the gap in local culinary demand research

Literature Review Conclusion

Based on the literature reviewed, it can be concluded that the LSTM method has advantages in processing time series data and is capable of capturing complex and dynamic demand patterns. However, studies that specifically apply LSTM in the context of forecasting demand for *kuliner Nusantara* in Indonesian marketplaces remain very limited. Therefore, this research seeks to fill that gap and provide a new contribution to the development of more accurate and contextual predictive models [21].

RESEARCH METHOD

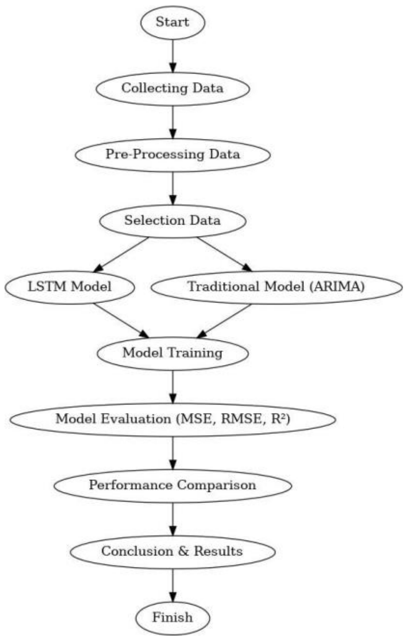

Figure 1. Research Stages.

Type of Research

This study employs a quantitative approach with a predictive method based on artificial neural networks, specifically Long Short-Term Memory (LSTM). The LSTM method was chosen because of its advantages in handling time series data and its ability to retain long-term historical patterns. This model is highly suitable for analyzing the instability of culinary product demand, which is dynamic and seasonal in nature [22].

Population

The population in this study consists of all sales data of culinary products from MSME partners selling through marketplaces (such as Shopee, Tokopedia, and GrabFood) during the period from 2022 to December 2024. The sample was selected using purposive sampling, namely monthly sales data that were completely documented throughout the period [23]. The use of purposive sampling aims to ensure that the data utilized are relevant, consistent, and reflect demand patterns that can be analyzed predictively.

Sample

The sample in this study consists of historical sales data of *kue kering Nusantara* products available in Indonesian marketplaces, specifically data that were recorded and archived from January 2022 to May 2024. Using a time series approach, the sample was taken in monthly time units, resulting in a total of 29 monthly data points that were used for model training and evaluation.

The sampling technique used in this study is time-based saturated sampling, which involves utilizing all available historical data during the research period without selecting or randomly extracting a portion of the data. This approach is commonly applied in LSTM-based predictive models, as data stability and continuity over time are crucial for training the model to capture temporal patterns [24].

The selection of this technique is intended to maximize the use of historical information and produce more representative predictions of trends and seasonal patterns in culinary product demand within Indonesian marketplaces [25].

Data Analysis Technique

The initial stage in data processing was data cleaning, which involved ensuring that the “Month” column was in date format and that the “Sales” column contained numerical values. The data were then aggregated by month to calculate the total culinary sales per month. Afterward, normalization was performed using MinMaxScaler to scale all values within the range of 0 to 1. This normalization process is essential for accelerating convergence during the LSTM model training.

The dataset was then structured into a time series window format using a sliding window method with a window size of 3, meaning that each input used the previous three months of data to predict the following month. Once the dataset was constructed, it was split into training data (80%) and testing data (20%). The training data were used to train the LSTM model, while the testing data were used to measure the model’s prediction accuracy.

Model Training

The LSTM model was built with an architecture consisting of one LSTM layer and one Dense layer. The training process was conducted for 100 epochs using the Adam optimizer and Mean Squared Error (MSE) as the loss function. During training, loss monitoring was carried out to avoid overfitting and to ensure the stability of predictions [26].

Model Evaluation

- Mean Squared Error (MSE) is calculated using the following formula:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_1)^2$$

Note:

Y_i = actual value
$\hat{Y}_1$ = predicted value
n = number of observations

- Root Mean Squared Error (RMSE) is the square root of MSE and is formulated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_1)^2}$$

RMSE provides a more interpretable measure because it has the same unit as the actual data.

- Coefficient of Determination (R^2) is calculated using the following formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_1)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

Note:

Y_i = actual value
$\hat{Y}_1$ = predicted value
$\bar{Y}$ = mean of the actual data

An R^2 value close to 1 indicates that the model is able to explain most of the variance in the actual data.

Conclusion & Results

These three metrics were used to compare the performance of the LSTM model with ARIMA. A model with lower MSE and RMSE values, as well as an R^2 value closer to 1, is considered to have better accuracy in predicting the demand for *kue kering Nusantara* products in marketplaces [27]. The findings of this study are expected to provide insights for business practitioners in optimizing product stock strategies, improving supply chain efficiency, and anticipating market demand fluctuations more accurately.

RESULTS AND DISCUSSION

Dataset Description

The study utilizes historical monthly sales data of *kue kering Nusantara* products available on the marketplace, specifically from Gemboel Cake. The dataset covers the period from January 2022 to May 2024, consisting of a total of 29 monthly observation points. The data were collected from internal sales reports exported in CSV format. Each entry in the dataset contains information on the sales month and the total sales recorded in units.

This study aims to forecast future demand trends using the Long Short-Term Memory (LSTM) approach. Therefore, the presence of well-structured time-series data is crucial. Preliminary observations indicate seasonal instability as well as significant upward and downward trends across the years [28].

The data used in this research are quantitative in nature and represent different types of *kue kering* products that exhibit seasonal demand characteristics. The researcher decided not to employ sampling techniques, as the dataset consists of the complete actual sales data available. In other words, this approach applies a census technique to the observation units [29].

Data Preprocessing

Before being used in the LSTM model training process, the raw data underwent a series of preprocessing steps. First, the data in the "Month" column was converted into a datetime format to enable time series analysis. Next, sales data from all products were aggregated by month to obtain the total monthly sales.

The subsequent step was data normalization using the Min-Max Scaling method. This process transformed sales values into a range between 0 and 1, which is essential to ensure stability and efficiency in training the LSTM network. In addition, the data were structured into a "sliding window" format to convert them into a three-dimensional dataset (samples, time steps, features), in accordance with the input requirements of the LSTM model [30].

A window size of three months was used, meaning that each input consisted of sales data from the previous three months to predict the following month. This process produced data pairs of X as features and **y** as targets, ready to be used for model training [31].

Visualization of Demand Trends

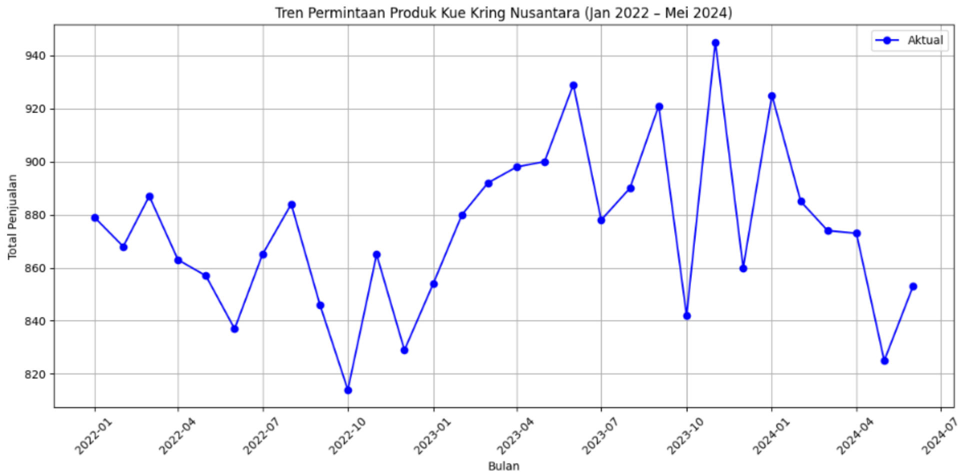

Figure 2. Demand Trends for Kue Kering Nusantara Products (January 2023 – May 2024).

The visualization of monthly demand trends for culinary products from January 2022 to May 2024 is presented to provide a general overview of sales fluctuations. The figure illustrates that demand tends to experience seasonal variations, with peaks occurring at the beginning of the year and declines toward the middle of the year.

Several demand spikes are observed in specific months, such as May 2023 and January 2024, which are likely influenced by seasonal factors such as holidays or promotional campaigns. Conversely, downward trends appear after peak periods, indicating the presence of cycles in consumer behavior. This graph serves as a visual foundation for developing the LSTM-based predictive model.

Training Progress

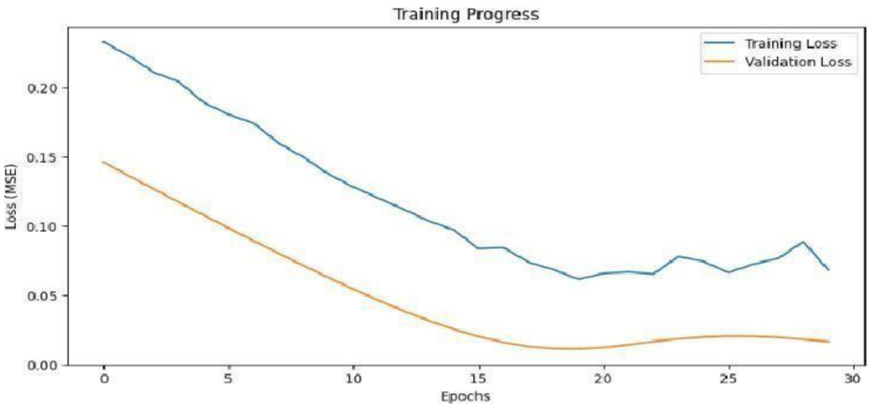

Figure 3. Training Progress.

The LSTM model used in this study consists of one LSTM layer with 50 neuron units and one Dense output layer. The model was trained using the Adam optimizer and the Mean Squared Error (MSE) loss function over 30 epochs.

The training results are visualized in a Training Progress graph, which shows a decreasing loss curve as the number of epochs increases. Both the training loss and validation loss decrease significantly and tend to stabilize after the 20th epoch. This indicates that the model successfully learned from the data without significant overfitting. The difference between the loss values on the training and validation datasets is also relatively small, suggesting that the model's generalization ability remains within an acceptable range [32].

Prediction Results Visualization

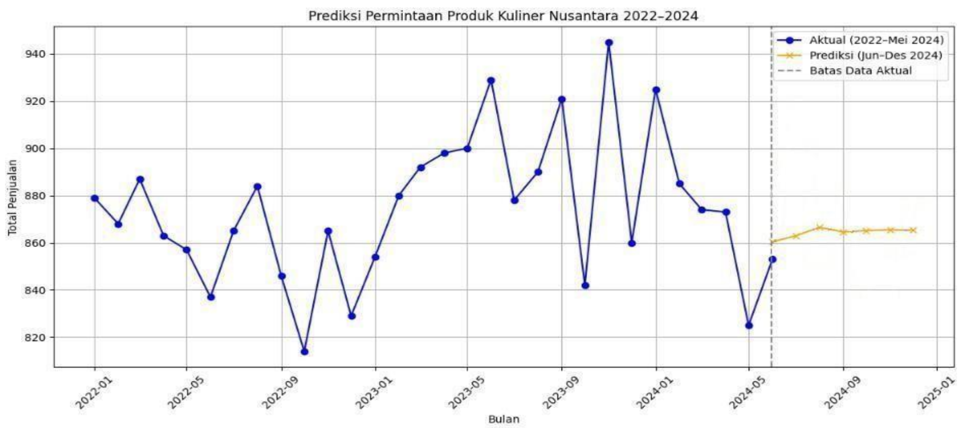

Figure 4. Forecasting the Demand for Kuliner Nusantara Products (2022–2024).

The visualization of prediction results presents a comparison between the actual data from January 2022 to May 2024 and the LSTM model predictions from January 2022 to December 2024. The blue line represents the actual data, while the orange line represents the predicted results.

It should be noted that the predictions from June to December 2024 are purely generated by the model, whereas the predictions from January 2022 to May 2024 are intended for model performance evaluation. The boundary between actual data and prediction is illustrated with a gray vertical line, marking the end of the observation data.

From this graph, it can be seen that the LSTM model successfully follows the seasonal patterns observed in the historical data. However, the predictions for the upcoming months indicate a relatively stagnant trend, which should be considered as a potential limitation of the model.

Model Evaluation (MSE, RMSE, and R^2)

The evaluation was carried out using three main metrics: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the Coefficient of Determination (R^2). The obtained values are as follows:

- MSE: 899.70
- RMSE: 30.00
- R^2: 0.09

The relatively large MSE value indicates a considerable difference between the actual and predicted values. The RMSE value of 30 further confirms consistent deviations of the model from the actual data. Finally, the low R^2 value demonstrates that the model was only able to explain 9% of the variance in the data, which means there is still room for improvement in enhancing model performance [33].

Nevertheless, this performance still provides a useful initial insight for estimating future demand patterns at a general level.

Practical Implications for MSMEs and Suggestions for Future Research

The findings of this study carry several important implications for culinary MSMEs, particularly those utilizing marketplaces as their primary distribution channels. Demand forecasting can assist MSMEs in managing raw material stock, planning promotions, and avoiding overstocking or understocking.

Although the model is not yet fully accurate, the LSTM approach has paved the way for small businesses to adopt predictive technologies in business decision-making. This is crucial, as the adaptability of MSMEs to digitalization greatly influences their business sustainability [34].

For future research, it is recommended to use a larger dataset, including weekly or daily data, to improve granularity. In addition, the model can be further developed by incorporating external variables such as weather, holidays, and customer reviews to enhance prediction accuracy. The use of hybrid models or integration with ARIMA is also worth considering as a potential comparative approach [35].

Model Weakness Analysis

The evaluation results indicate that the LSTM model still has several significant limitations. First, the low R^2 value suggests that the model has not yet been able to effectively capture the complex temporal relationships. This may be due to the limited amount of data, with only about 29 monthly observations available, which is insufficient to optimize the parameters of the LSTM model [36].

Second, the long-term predictions from June to December 2024 display a relatively stagnant trend and fail to adequately reflect seasonal dynamics. This is most likely because the model loses signal variability as a result of normalization or due to the lack of new input signals in the data. Moreover, the model does not take into account external factors such as promotional campaigns, holiday seasons, or consumer behavior, all of which may significantly influence demand [37].

CONCLUSION

Fundamental Finding : This study demonstrates that the Long Short-Term Memory (LSTM) model effectively captures temporal patterns within the dataset. **Implication :** The effective temporal learning capability of the LSTM model suggests its suitability for forecasting tasks requiring sequential pattern recognition. **Limitation :** The model's performance may be constrained by data quality, computational cost, and potential overfitting on limited datasets. **Future Research :** Future studies should explore hybrid architectures, larger and more diverse datasets, and optimization techniques to further enhance LSTM performance.

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