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Research Article

An Analysis of Time-Series Forecasting Models for Optimizing School-Based Feeding Programs

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ABSTRACT

Accurately forecasting meal demand in School-Based Feeding Programs (SBFPs) is essential for enhancing program efficiency and minimizing food waste. This study assessed the performance of four predictive models—ARIMA, Long Short-Term Memory (LSTM), Prophet, and Random Forest Regression—in forecasting daily attendance for SBFPs. Attendance data from eight schools within the Tarlac City Schools Division, spanning August 19 to October 19, 2024, were used. The LSTM model demonstrated superior predictive accuracy, achieving the lowest RMSE (5.51), MAE (4.91), and sMAPE (0.27%), making it the most effective model. Prophet followed closely with an RMSE of 5.89, MAE of 4.96, and sMAPE of 0.27%. Random Forest Regression showed moderate performance with an RMSE of 6.56 and MAE of 5.19, while ARIMA underperformed significantly with an RMSE of 435.60 and MAE of 392.43. These findings highlight the potential of AI-driven forecasting models like LSTM to optimize resource allocation, reduce food waste, and improve the operational efficiency of SBFPs.

Keywords: School-based feeding program, forecasting, lstm, arima, prophet.

INTRODUCTION

School-Based Feeding Programs (SBFPs) are critical for addressing food security and enhancing child development and nutrition, particularly in vulnerable communities[1]. These are intended to treat temporary hunger, improve children's nutrition and cognitive abilities, and provide financial relief to families[2]. SBFPs have been steadily gaining popularity in developing nations, particularly among those heavily affected by childhood malnutrition. These initiatives aim to improve schoolchildren's concentration and learning abilities by providing meals in schools to alleviate short-term hunger, which can otherwise hinder children's academic performance[3]. In the Philippines, the Department of Education has implemented SBFPs to address hunger and malnutrition among school-aged children, contributing significantly to improved educational outcomes[4]. However, these programs face ongoing challenges in predicting meal demand accurately[5], leading to either food waste or meal shortages [6], [7], [8]which ultimately impacts the overall effectiveness of the program.

One of the primary obstacles in SBFPs is aligning food procurement and preparation with actual demand, a task complicated by fluctuating attendance rates, diverse dietary needs, and variable school schedules. Predicting daily attendance accurately is crucial because over-preparing meals results in food waste, while under-preparing leaves some students without their share of the prepared food. Implementing advanced predictive analytics and machine learning models can potentially resolve these issues by forecasting demand more effectively. Despite the adoption of technology in various industries for optimizing supply chain logistics, school feeding programs still rely on manual methods or simplistic forecasting approaches that do not adequately account for the dynamic nature of attendance

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and meal requirements[5]. Addressing this gap in SBFP operations is key to improving program efficiency and sustainability, as more precise forecasts can reduce food waste and ensure that every student in need receives a meal.

Several established AI models, including Autoregressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), Random Forest Regression, and Prophet, are explored for their potential to enhance meal preparation demand forecasting in SBFPs. ARIMA models are effective in capturing temporal dependencies in time series data but may fall short when dealing with complex non-linear patterns[9]. Random Forest Regression, utilizing multiple decision trees for prediction, is susceptible to overfitting if not carefully tuned[10], [11]. The Prophet model, specifically designed for time series data, excels at handling seasonality and trend changes[12] but may lack the flexibility of other models in capturing intricate data relationships[13].

Furthermore, the need to tailor these AI models to the specific demands of SBFPs is critical for ensuring accurate forecasting. Variables such as student demographics, school calendars, and meal program structures vary significantly from one region to another, requiring models that are adaptive to these factors. Research in food waste management in school nutrition programs has been limited, often employing different methodologies and yielding inconsistent findings, which complicates the development of standardized best practices. There is a growing need for models that can generalize well across diverse SBFP settings while maintaining high accuracy, as this would significantly reduce inefficiencies and food waste while promoting better resource allocation[14], [15].

LSTM networks show the greatest promise for improving demand forecasting in SBFPs. LSTMs, a form of recurrent neural network, are designed to learn long-term dependencies from sequential data, as evidenced in studies by [5] and [10]. This makes them particularly suitable for capturing the complex patterns and trends inherent in SBFP meal demand. Unlike ARIMA and Prophet, which rely on predefined statistical relationships[13], LSTMs can learn complex non-linear relationships directly from the data, leading to potentially more accurate predictions[9]. Additionally, LSTMs are capable of handling missing data points and irregular time intervals, common occurrences in SBFP datasets[5].

The goal of this study is to address these challenges by examining existing AI models and applying the most suitable model to a demand forecasting framework to improve meal preparation accuracy and reduce food waste in SBFPs. Specifically, this research identifies and compares various AI models that can enhance meal preparation demand in SBFPs, highlighting each model's strengths and limitations. It also analyzes the impact of these AI models on improving meal preparation demand using key performance indicators and develops an AI model that successfully tracks and analyzes SBFP resources by using LSTM capabilities.

METHODS AND METHODOLOGY

This study utilized attendance data collected from eight (8) schools within the Tarlac City Schools Division of the Philippine Department of Education. The dataset covered the daily attendance of learners participating in the School-Based Feeding Program (SBFP) from August 19, 2024, to October 19, 2024. It comprised a total of 83,566 attendance records from 1,857 learners, ranging from Kindergarten to Grade 6.

Data collection was carried out through an online submission form completed by the SBFP focal persons of each school. To ensure the accuracy and completeness of the records, the submissions were verified through personal visits to the respective schools. Each entry in the dataset contained detailed information, including the date, the number of attendees, and the specific school to which the record belonged.

The dataset underwent preprocessing to address inconsistencies such as missing values or erroneous entries. The cleaned dataset was then split into two subsets: 70% for training and 30% for testing, following a widely accepted practice in predictive analytics. This split ensured that the model had sufficient data to learn patterns while reserving a portion for evaluating its performance.

Table 1. Number of Beneficiaries and Attendance per School

School Name	No. of Beneficiaries	No. of Attendance
Alvindia Elementary School	**58**	**2,667**
Matatalaib Bato Elementary School	**334**	**15,169**
San Carlos Elementary School	**64**	**2,898**
San Jose Elementary School	**207**	**9,372**
San Miguel Central Elementary School	**387**	**17,428**
Sta. Cruz Elementary School	**95**	**4,064**
Tarlac West Elementary School	**459**	**20,727**
Tibag Elementary School	**253**	**11,241**
TOTAL	**1,857**	**83,566**

In this study, four time-series forecasting models were used to predict daily attendance in the School-Based Feeding Program (SBFP): ARIMA, PROPHET, Random Forest Regression, and Long Short-Term Memory (LSTM). These models were chosen for their ability to handle different types of data patterns and trends. ARIMA was selected for its capacity to model linear relationships and seasonal trends in stationary time series, while PROPHET was included due to its robustness in modeling seasonality and handling irregular data points. Random Forest Regression was chosen for its effectiveness in managing complex, non-linear data relationships, making it suitable for real-world scenarios with varied attendance patterns. Lastly, LSTM, a deep learning model, was used for its ability to capture long-term dependencies, making it ideal for sequential time-series forecasting.

The implementation of these models was carried out using Python within the Visual Studio Code IDE. For data preparation and manipulation, the pandas and numpy libraries were employed to clean, transform, and organize the dataset for effective analysis. The ARIMA model was constructed using the statsmodels library, while the PROPHET model was developed with the fbprophet library. For Random Forest Regression, the scikit-learn library was utilized, and LSTM was implemented using the tensorflow and keras libraries. Visualization of data trends and model outputs was achieved using matplotlib and seaborn, providing a clear representation of the forecasted results.

The performance of these models was assessed using various error metrics, including RMSE, MAE, MAPE, sMAPE, and MASE. These metrics were chosen to capture the accuracy of predictions, both in terms of absolute errors and percentage-based deviations. By evaluating each model through these comprehensive metrics, this study aimed to determine the most accurate forecasting method, optimizing food procurement and minimizing waste in the SBFP. The selected models and metrics ensure that the predictions made align with the practical needs of the program, ultimately contributing to better resource allocation and decision-making.

RESULTS AND DISCUSSION

The data in this study was split using a 70/30 ratio for training and testing, a widely accepted practice in predictive analytics. This ratio allows the model to learn from a substantial portion of the dataset (70%), ensuring it captures essential patterns and relationships, while still having a sufficient portion (30%) reserved for testing, enabling an accurate assessment of its predictive performance. The choice of this split ensures that the model has enough data for training, which is particularly important when dealing with temporal and sequential data, as in the case of School-Based Feeding Programs (SBFP). This split also helps balance the need to prevent overfitting while maintaining a robust testing ground for evaluation.

Several performance metrics were used to evaluate the models: RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MAPE (Mean Absolute Percentage Error), sMAPE (Symmetric Mean Absolute Percentage Error), and MASE (Mean Absolute Scaled Error). These metrics were chosen for their ability to provide insights into different aspects of the model's accuracy and robustness. RMSE and MAE give an understanding of the model's absolute predictive accuracy, with RMSE penalizing larger errors more heavily, making it particularly useful in scenarios

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where outliers or large deviations are critical to capture. On the other hand, MAPE and sMAPE are percentage-based errors, which are essential for understanding the relative accuracy of the model, especially in cases where the magnitude of errors must be scaled in comparison to the actual values. Finally, MASE provides an overall scale-independent error measurement, offering a benchmark against which other forecasting methods can be compared, making it suitable for comparing model performance across various datasets.

From the results as shown in Table 2, it is evident that the LSTM model demonstrated the best overall performance, with the lowest RMSE (5.51) and MAE (4.91), and competitive results across MAPE, sMAPE, and MASE. This indicates that LSTM, with its ability to capture complex temporal dependencies, was particularly effective in predicting SBFP meal demand. The ARIMA model, in contrast, performed poorly, with a significantly higher RMSE (435.60) and MAE (392.43), reflecting its limitation in handling non-linear patterns prevalent in the data. Prophet and Random Forest Regression performed moderately well, with Prophet slightly outperforming Random Forest Regression. Prophet's strength in handling seasonality contributed to its low error rates, while Random Forest's flexibility with decision trees provided a good, albeit slightly less accurate, performance compared to LSTM. These findings highlight the importance of selecting models that can adapt to the specific characteristics of SBFP data for effective demand forecasting.

Table 2. Number of Beneficiaries and Attendance per School

Model	RMSE	MAE	MAPE	sMAPE	MASE
ARIMA	**435.5967**	**392.4291**	**inf%**	**61.3810%**	**0.7983**
LSTM	**5.51234**	**4.91537**	**0.2726%**	**0.2723%**	**0.6057**
PROPHET	**5.8866**	**4.9617**	**0.2743%**	**0.2747%**	**0.5725**
RANDOM FOREST REGRESSION	**6.5640**	**5.1857**	**0.2874%**	**0.2868%**	**0.5984**

The comparative analysis of four predictive models—ARIMA, Prophet, Regression, and LSTM—using various performance metrics, including RMSE, MAE, MAPE, sMAPE, and MASE. The ARIMA model exhibits significantly higher RMSE and MAE values, indicating poor performance in terms of accuracy compared to the other models. The MAPE for ARIMA is recorded as "inf%" due to the high prediction error, especially in cases where the actual values are small or zero, making the error percentage infinite. In contrast, the Prophet and LSTM models demonstrate similar and significantly better performance with lower RMSE, MAE, and MAPE, reflecting higher prediction accuracy. Prophet's slightly lower MASE and sMAPE compared to LSTM suggests a marginal advantage in terms of relative error. Overall, LSTM and Prophet models are the most efficient in predicting attendance in this dataset, while ARIMA underperforms considerably, suggesting that nonlinear models may better capture trends in the attendance data as shown in figure 1.

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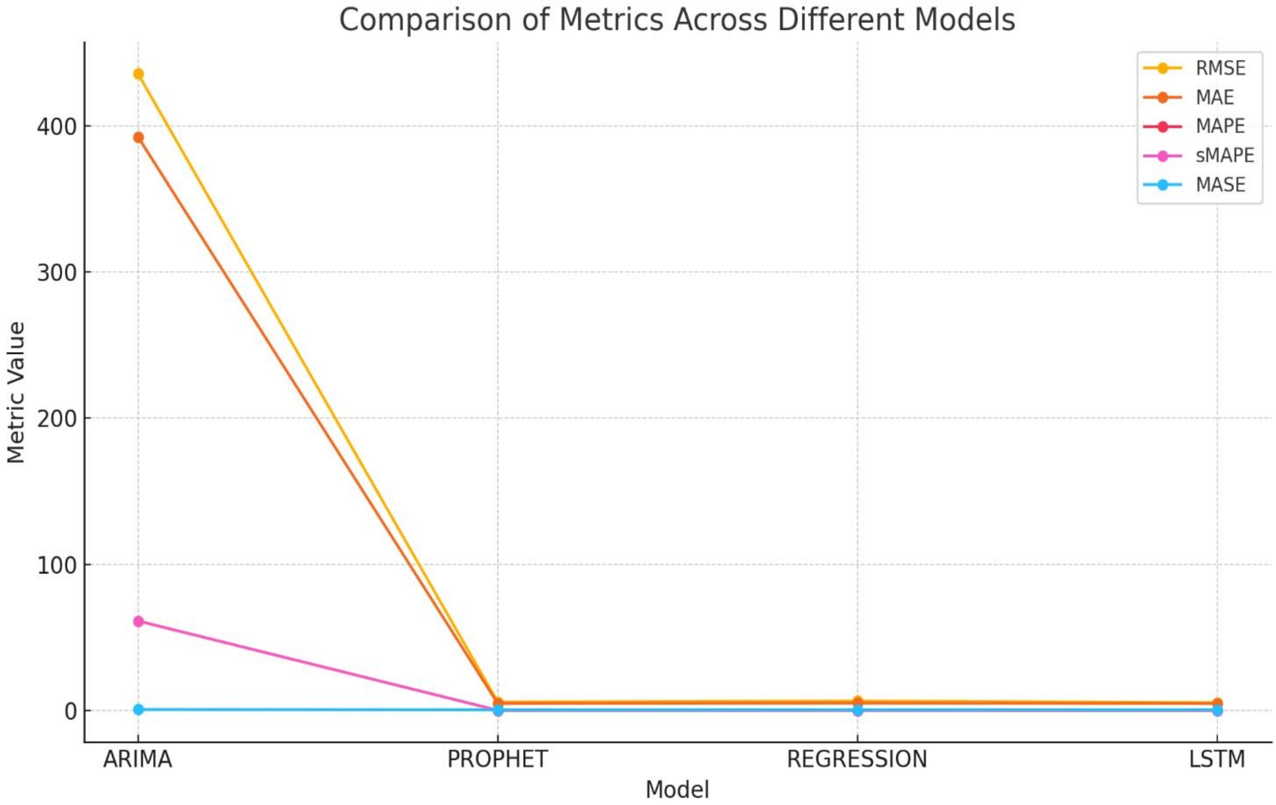

Figure 1 Comparison of metrics across the four (4) models

CONCLUSION

This study explored the application of four predictive models—ARIMA, LSTM, Prophet, and Random Forest Regression—in forecasting attendance for the School-Based Feeding Program (SBFP) to improve meal demand accuracy and reduce food waste. The findings reveal that the LSTM model outperformed the others across all key metrics, demonstrating its capacity to capture complex non-linear and temporal patterns inherent in the data. Prophet, while highly competitive, particularly in handling seasonality, also performed well but fell slightly short compared to LSTM in terms of overall accuracy. Random Forest Regression, known for its flexibility, provided decent results, but it was less effective in modeling the intricate relationships in the attendance data. ARIMA, on the other hand, performed poorly, showing limitations in addressing non-linearities in the data. These results emphasize the importance of selecting models that can capture both temporal dependencies and non-linear patterns for SBFP demand forecasting. Implementing advanced machine learning models, such as LSTM, can significantly enhance program efficiency, reduce food waste, and ensure adequate meal provision to students, ultimately contributing to better educational outcomes.

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Data Availability:

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflict of Interest:

The authors declare that there is **no conflict of interest.**

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