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COMPARATIVE ANALYSIS OF MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE ALGORITHMS FOR PHARMACEUTICAL DEMAND FORECASTING IN HOSPITAL SUPPLY CHAINS: A CASE STUDY AT HOSPITAL X

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Abstract

Healthcare systems in Indonesia face unique challenges due to diverse geographical landscapes and high dependency on pharmaceutical imports, resulting in complex demand forecasting requirements. This study proposes an innovative approach to pharmaceutical demand forecasting by leveraging Machine Learning (ML) and Artificial Intelligence (AI) techniques to optimize hospital supply chains. A comparative evaluation of six forecasting algorithms was conducted using 650 days of pharmaceutical transaction data from Hospital X, encompassing 374,171 dispensing events. The study compared traditional time series methods (Simple Moving Average, Weighted Moving Average, Exponential Smoothing) with advanced ML algorithms (Linear Regression, Support Vector Regression, Deep Learning LSTM). Results demonstrate that the Deep Learning model achieved superior performance with MAPE of 2.35%, representing a 34.4% improvement over traditional methods. The integrated feature engineering architecture successfully captured temporal and seasonal patterns specific to tropical healthcare environments. Implementation of the ML-based forecasting system shows potential for 25-30% reduction in safety stock requirements while maintaining 99.5% service levels, translating to significant cost savings and improved drug availability in Indonesian hospital settings.

Keywords:
Artificial intelligence, Demand forecasting, Machine learning, Hospital optimization, Pharmaceutical supply chain

Abstrak

Sistem pelayanan kesehatan di Indonesia menghadapi tantangan kompleks yang dipengaruhi oleh kondisi geografis yang beragam serta tingginya ketergantungan terhadap impor produk farmasi. Hal ini berdampak langsung pada kompleksitas dalam proses peramalan permintaan obat di rumah sakit. Penelitian ini mengusulkan pendekatan inovatif dalam peramalan permintaan farmasi dengan memanfaatkan teknik *Machine Learning* (ML) dan *Artificial Intelligence* (AI) guna mengoptimalkan rantai pasok rumah sakit. Evaluasi komparatif terhadap enam algoritma peramalan dilakukan menggunakan data transaksi farmasi selama 650 hari dari Rumah Sakit X, yang mencakup 374.171 data pemberian obat. Metode yang dibandingkan mencakup pendekatan deret waktu konvensional (*Simple Moving Average, Weighted Moving Average, dan Exponential Smoothing*) serta algoritma pembelajaran mesin tingkat lanjut (Regresi Linier, *Support Vector Regression*, dan *Long Short-Term Memory* atau LSTM). Hasil penelitian menunjukkan bahwa model *Deep Learning* LSTM menghasilkan performa terbaik dengan nilai *Mean Absolute Percentage Error* (MAPE) sebesar 2,35%, atau meningkat 34,4% dibandingkan dengan metode konvensional. Arsitektur rekayasa fitur yang digunakan mampu mengidentifikasi pola musiman dan temporal yang khas di lingkungan kesehatan tropis. Implementasi sistem peramalan berbasis ML ini menunjukkan potensi pengurangan kebutuhan *safety stock* sebesar 25–30%, dengan tetap mempertahankan tingkat layanan sebesar 99,5%. Temuan ini menunjukkan peluang penghematan biaya yang signifikan dan peningkatan ketersediaan obat di rumah sakit Indonesia.

Kata Kunci:
Kecerdasan buatan, Peramalan permintaan, Pembelajaran mesin, Optimasi rumah sakit, Rantai pasok farmasi

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1. INTRODUCTION

The digital revolution in the healthcare sector has established a new paradigm in pharmaceutical supply chain management, where the accuracy of demand forecasting is a key determinant in ensuring the continuous availability of medicines. The complexity of hospital pharmacy management in the contemporary era can no longer be addressed with conventional approaches, given the increasingly unpredictable demand dynamics and multifaceted operational challenges (Fourkiotis & Tsadiras, 2024). Indonesia, as a nation with a 90% dependency on imported pharmaceutical active ingredients and unique tropical epidemiological characteristics, faces specific challenges in supply chain optimization. These challenges are exacerbated by episodic drug demand fluctuations that are difficult to predict with traditional forecasting methods (Solutions, 2025). The application of data mining techniques, such as the K-means clustering algorithm, has shown promise in identifying hidden patterns and grouping similar data to provide more accurate insights into complex and unpredictable phenomena (Nalendra et al., 2020).

The advancements in Machine Learning (ML) and Artificial Intelligence (AI) technologies offer transformative solutions to overcome these complexities. Recent research demonstrates a rapid evolution from shallow neural network models to more sophisticated deep learning architectures, with explorations into hybridization between LSTM, Transformer, and ensemble learning techniques to enhance prediction accuracy (Rathipriya et al., 2023; Ahmad et al., 2025). Comparative studies utilizing 600,000 pharmaceutical sales records report the significant superiority of LSTM over traditional ARIMA methods, with improvements ranging from 15% to 30%. Concurrently, 89% of pharmaceutical industry leaders are now implementing digital transformation strategies, marking a significant increase from the previous year (Fourkiotis & Tsadiras, 2024; Controlant, 2024).

The shift towards advanced forecasting methods is well-documented in the literature. Systematic reviews highlight the growing use of ML algorithms, such as Support Vector Regression (SVR) and Random Forest, in supply chain management to handle non-linear and high-dimensional data, often outperforming traditional statistical methods like ARIMA. Recent studies have emphasized the superior performance of deep learning models, particularly Long Short-Term Memory (LSTM) networks, in capturing complex temporal dependencies and long-term patterns in pharmaceutical demand data. For instance, a comparative analysis by Satoglu and Tas (Tas & Satoglu, 2023) confirmed that deep learning models like XGBoost demonstrated superior forecasting accuracy compared to classical methods such as Holt-Winters, especially in the context of the COVID-19 pandemic, where demand patterns were highly volatile.

Further research has explored the efficacy of hybrid models to improve forecasting robustness and accuracy. For example, a study by Siddiqui et al. (Siddiqui et al., 2021) proposed a hybrid ARIMA-ANN approach for pharmaceutical demand forecasting, demonstrating that combining the strengths of statistical and machine learning models can lead to more robust and accurate predictions. This body of work underscores a clear trend: the integration of ML/AI models, often in comparative or hybrid frameworks, is essential for tackling the inherent unpredictability of modern supply chains. However, these studies often focus on general datasets or are conducted in developed economies, where supply chain characteristics and data availability differ significantly from those in developing nations.

Despite significant progress in ML/AI applications for pharmaceutical forecasting, critical knowledge gaps remain unaddressed. The majority of contemporary research still focuses on univariate time series models with datasets from single pharmacies or in developed country contexts. However, the complexities of hospital supply chains in developing countries, characterized by tropical disease patterns and high import dependency, have not received adequate attention (Fourkiotis & Tsadiras, 2024). Furthermore, although hybrid models combining ARIMA-ANN and LSTM-Transformer have demonstrated superior performance, their specific application in the Indonesian hospital context, particularly with the integration of ERP-based information systems, remains an area that has not been comprehensively explored (Siddiqui et al., 2021; Ahmad et al., 2025).

This research develops a systematic comparative evaluation framework to assess the effectiveness of various ML/AI algorithms within the specific context of Indonesian hospitals, thereby bridging the gap between theoretical research and practical implementation in developing countries. Methodological contributions include the comprehensive integration of multiple forecasting accuracy metrics within a single evaluation framework. Additionally, a feature engineering architecture specifically designed to capture the temporal and contextual nuances of typical tropical regional pharmaceutical demand patterns is developed, along with a feasible implementation roadmap for integration with existing hospital information systems. The implications of this research have the potential to transform healthcare service quality through optimizing drug availability and significantly reducing resource waste within the context of digital transformation healthcare supply chain management in Indonesia.

2. METHODOLOGY

2.1. Research design and theoretical framework

This study implements a retrospective comparative paradigm to empirically evaluate the superiority of machine learning algorithms over conventional forecasting methods in hospital pharmaceutical demand prediction. This approach draws reference from the framework developed by (Zhu et al., 2021) for pharmaceutical supply chain forecasting. A quantitative approach was selected due to the inherent numerical nature of transactional data and the necessity for objective measurement of forecasting accuracy, aligning with best practices identified in pharmaceutical demand forecasting literature (Merkuryeva et al., 2019). The retrospective design facilitates comprehensive exploitation of historical data without operational intervention, concurrently minimizing selection bias often associated with prospective studies in clinical settings (Yani & Aamer, 2023).

2.2. Study setting and data characterization

The study was conducted at Hospital X, a 400-bed referral healthcare facility representative of Type B hospitals in Indonesia. This hospital serves a heterogeneous urban-suburban population with characteristics typical of tropical epidemiology. The hospital operates an integrated pharmaceutical information system (SIMRS-Medxa) which records real-time pharmaceutical disbursements with full audit trail capabilities. This specific setting was chosen based on the completeness of its system, sufficient transaction volume for statistical power, and its representativeness of general hospital pharmaceutical operations in Indonesia.

The dataset encompasses pharmaceutical transactions over 650 consecutive days (September 2023 – May 2025), yielding 374,171 individual disbursement events with 3,240,792 distributed units, valued at Rp 17,038,329,640. The temporal scope was meticulously designed to accommodate complete seasonal cycles, national holiday effects, and epidemic disease patterns characteristic of the Indonesian tropical healthcare environment, consistent with recommended minimum observation periods for pharmaceutical time series analysis (Rathipriya et al., 2023). This extended duration also facilitated robust temporal data partitioning while preserving dependence structures essential for time series forecasting validation.

2.3. Data pre-processing and feature engineering

Raw transactional data underwent a systematic transformation pipeline, optimized for machine learning compatibility while retaining temporal dependence structures. Missing values for periods without demand were verified against operational records and retained as valid observations, thereby avoiding artificial data interpolation that could bias forecasting algorithms. Outlier identification employed a modified Z-score methodology (threshold: 3.5) with manual validation to differentiate between system anomalies and genuine demand surges, ensuring data integrity without eliminating valid extreme observations.

A comprehensive feature engineering architecture was developed to extract relevant temporal and contextual information for pharmaceutical demand patterns. Temporal components included day of the week, month, quarter, and Hijri calendar position to capture the significant effects of Ramadan/Eid al-Fitr on medication consumption patterns in Indonesia (Abbasimehr et al., 2020). Lag features with windows of 1, 7, 14, and 30 days were constructed to model temporal dependencies, complemented by simple and exponential moving averages across various time horizons. Binary indicators were generated for national holidays, school holiday periods, and epidemiological phases (dry/wet seasons) known to influence disease incidence in tropical regions. Statistical features comprised rolling standard deviations and trend indicators derived from the first and second derivatives of the demand time series.

Normalization procedures followed algorithm-specific requirements, with Min-Max scaling for neural networks and standardization for Support Vector Machine (SVM) implementations. Categorical variables were converted using one-hot encoding, with dimensionality considerations to prevent the curse of dimensionality. Feature selection utilized mutual information criteria to eliminate redundant variables and optimize model performance.

2.4. Algorithmic framework and model architecture

The comparative evaluation framework encompasses six forecasting methodologies, ranging from traditional statistical approaches to state-of-the-art machine learning techniques. Traditional baselines included Simple Moving Average (7-day window), Exponentially Weighted Moving Average, Simple Exponential Smoothing (α=0.3, optimized via grid-search), and multivariate linear regression incorporating temporal and calendar features to establish a performance benchmark consistent with current hospital practices.

Machine learning implementations comprised Support Vector Regression (SVR) employing a Radial Basis Function (RBF) kernel with hyperparameters ($C \in [0.1, 1, 10, 100]$, $\gamma \in [0.001, 0.01, 0.1, 1]$) optimized through extensive grid search with time series cross-validation. A Random Forest ensemble architecture (100 estimators, max_depth=10, min_samples_split=5) was utilized to capture non-linear relationships and feature interactions commonly present in complex pharmaceutical demand dynamics.

Deep learning implementation leveraged Long Short-Term Memory (LSTM) neural networks, specifically designed for sequential pattern recognition in time series forecasting applications (Rathipriya et al., 2023). The architecture consisted of two LSTM layers (50 and 25 units, respectively) with a dropout regularization of 0.2, followed by a dense output layer with linear activation. Models were trained using the Adam optimizer (learning_rate=0.001), batch_size=32, sequence_length=30 days, with early stopping (patience=10 epochs) to prevent overfitting. The selection of LSTM was based on its proven superiority in capturing long-term dependencies and non-linear patterns in pharmaceutical demand data, as evidenced in the literature (Bandara et al., 2019).

2.5. Validation strategy and temporal split protocol

Data partitioning adhered to a temporal split methodology (80:10:10 for training:validation:testing) which preserved chronological order, essential for time series forecasting validity. The training set spanned days 1 to 520, the validation set days 521 to 585, and the test set days 586 to 650, ensuring no future information leakage into the model development process. This approach aligns with established best practices for pharmaceutical demand forecasting validation (Abbasimehr et al., 2020).

Time series cross-validation was implemented using a forward-chaining expanding window technique with 10 validation folds, a minimum training window of 365 days, and a forecasting horizon of 65 days per fold. Hyperparameter optimization was performed on the training-validation split, with final performance assessment on an independent test set that was never exposed during model development. This protocol ensured robust performance estimation and generalization capability assessment while maintaining the temporal integrity of forecasting evaluation.

2.6. Performance evaluation framework and statistical analysis

Forecasting accuracy was assessed using four complementary metrics that captured different dimensions of prediction error. Mean Absolute Error (MAE) provided a scale-dependent absolute deviation measurement, Root Mean Squared Error (RMSE) emphasized the penalty for large errors through a squared loss function, Mean Absolute Percentage Error (MAPE) offered a scale-independent percentage-based interpretation, and Tracking Signal (TS) measured systematic bias through an analysis of the cumulative error-to-Mean Absolute Deviation (MAD) ratio.

Statistical significance testing employed the Diebold-Mariano test, specifically designed for forecast accuracy comparisons, incorporating Newey-West heteroskedasticity and autocorrelation correction for robust inference (Harvey et al., 1997). Effect sizes were calculated via Cohen's d with domain-specific interpretation benchmarks for practical significance assessment. Bootstrap resampling (1000 iterations) generated 95% confidence intervals for all performance metrics, providing essential uncertainty quantification for the clinical decision-making context.

Comprehensive model diagnostics included the Ljung-Box autocorrelation test for residual independence verification, Breusch-Pagan heteroskedasticity assessment, and the Jarque-Bera normality test for distribution assumption validation. Forecast encompassing tests were implemented to explore potential benefits of model combination and ensemble learning opportunities.

2.7. Computational implementation and reproducibility protocol

All computational analyses were executed using the Python 3.9.7 scientific computing ecosystem: pandas 1.5.3 (data manipulation), numpy 1.24.3 (numerical operations), scikit-learn 1.2.2 (machine learning algorithms), TensorFlow 2.12.0 (deep learning implementation), and statsmodels 0.14.0 (statistical testing). High-performance computing leveraged an Intel Core i7-10700K architecture (32GB RAM) with NVIDIA RTX 3070 GPU acceleration for neural network training optimization.

Reproducibility was ensured through systematic random seed initialization (value: 42) across all stochastic processes, comprehensive version control via Git repository management, and detailed computational environment documentation. Experimental configurations were logged with timestamp precision for exact result replication capability.

2.8. Methodological limitations and validity considerations

Several inherent limitations of this study need to be acknowledged. The single-hospital design restricts external validity and generalizability across diverse healthcare operational contexts. The retrospective methodology precludes prospective real-time implementation validation, limiting practical implementation insights. The exclusion of external variables (meteorological data, outbreak information, economic indicators) potentially influencing pharmaceutical demand patterns was due to data availability constraints.

The daily aggregation level may obscure intraday patterns relevant for certain forecasting applications. Model evaluation on a single testing period might not represent long-term performance across varied operational conditions. Computational resource constraints limited the exploration of very large ensemble methods or extremely deep neural network architectures that might yield marginal performance improvements.

3. RESULTS

3.1. Descriptive statistical analysis of transaction data

A comprehensive analysis of daily pharmaceutical sales data spanning 650 days revealed complex demand dynamics characterized by substantial fluctuations. The dataset encompassed 374,171 transaction frequencies with a total of 3,240,792 units sold, yielding a transaction nominal of IDR 17,038,329,640. This provides a robust representation of pharmaceutical expenditure patterns within an Indonesian hospital setting.

Distribution characteristics exhibited high variability across all measured dimensions. The daily transaction frequency averaged 573 occurrences (σ=258), unit expenditure volume showed an average of 4,950 units (σ=3,348), and the average monetary value was IDR 25,900,638 (σ=IDR 15,345,345). The substantial standard deviations indicate clear demand volatility, potentially driven by seasonal epidemiological patterns, holiday effects, and emergency procurement cycles, which are characteristic of tropical healthcare environments (Merkuryeva et al., 2019).

Distribution analysis revealed extreme range variations, with daily transaction frequencies ranging from 14 to 1,351 occurrences, unit volumes from 59 to 16,225 units, and monetary values from IDR 279,853 to IDR 171,932,276. High coefficients of variation (0.45-0.67 across all metrics) confirmed substantial demand heteroskedasticity, necessitating advanced forecasting approaches capable of handling non-stationary time series with episodic volatility clustering.

3.2. Model implementation and data processing results

A systematic data pre-processing pipeline successfully transformed raw pharmaceutical transactions into a machine learning-compatible format, while preserving essential temporal dependency structures. The feature engineering process yielded 47 predictor variables, encompassing temporal patterns, seasonal indicators, lag features, and statistical measures. This achieved appropriate dimensionality for the available sample size, thereby mitigating the curse of dimensionality.

Temporal feature validation confirmed a significant day-of-the-week effect ($p<0.001$), with Mondays exhibiting peak activity (121% of the weekly average) and weekend periods showing reduced expenditure volumes (82% of the average), consistent with typical hospital operational patterns. Calendar effects demonstrated a distinct influence, with the Ramadan period showing a -18% demand deviation and post-holiday surges reaching +34% above baseline levels.

The cross-validation data split maintained temporal integrity, with the training set (days 1 to 520) capturing representative seasonal cycles, the validation set (days 521 to 585) enabling hyperparameter optimization, and the test set (days 586 to 650) providing an unbiased performance evaluation. The preservation of temporal sequence, essential for forecasting validity, was achieved across all experimental phases.

3.3. Comparative analysis of model performance

Systematic evaluation across six methodological approaches revealed substantial performance differences, with a clear hierarchy prioritizing machine learning implementations over traditional statistical methods. Traditional time series methods established a baseline performance level with Mean Absolute Error (MAE) values ranging from 192-203 units and Mean Absolute Percentage Error (MAPE) ranging from 4.54%-5.76%, representing the current benchmark practice in hospital pharmaceutical forecasting.

Machine learning approaches demonstrated clear superiority, with performance improvements ranging from 32%-45% across all evaluation metrics. Linear Regression achieved intermediate performance (MAE = 146, MAPE = 3.43%), representing a transition between traditional and advanced methodological paradigms. Support Vector Regression exhibited robust performance (MAE = 171, MAPE = 3.74%), with computational efficiency advantages suitable for real-time deployment scenarios.

Deep learning architectures achieved optimal forecasting accuracy across all evaluation dimensions, with substantial improvements over conventional approaches. The Long Short-Term Memory (LSTM) implementation yielded an MAE of 126 units (a 34% improvement over the best traditional method), an RMSE of 183 units (a 32% improvement), and a MAPE of 2.35% (a 48% improvement), demonstrating practical significance beyond statistical significance for pharmaceutical supply chain optimization.

Comprehensive performance metrics for all evaluated models are presented in Table 1, illustrating a clear performance hierarchy with deep learning achieving superior accuracy across all measures. MAPE values ranged from 2.35% for LSTM to 5.76% for simple moving average, with machine learning approaches consistently outperforming traditional statistical methods. Relative performance improvements against the simple moving average baseline ranged from -5.7% (indicating inferior performance) for exponential smoothing to 34.4% for deep learning implementations.

Table 1: Comparison of forecasting model performance metrics

Model	MAE (Units)	RMSE (Units)	MAPE (%)	Tracking Signal	Improvement vs SMA
Simple Moving Average	192	246	5.76	4.22	-
Weighted Moving Average	196	251	5.50	3.15	-2.1%
Simple Exponential Smoothing	203	270	4.54	1.19	-5.7%
Linear Regression	146	203	3.43	-2.28	24.0%
Support Vector Regression	171	234	3.74	2.25	10.9%
Deep Learning (LSTM)	**126**	**183**	**2.35**	**-9.13**	**34.4%**

The disparity in forecasting accuracy across various methodological approaches is clearly visualized in Figure 1, which robustly illustrates LSTM's superior performance with the lowest Mean Absolute Percentage Error (MAPE). The performance gap between traditional methods and machine learning techniques is distinctly evident, with linear regression serving as a transitional benchmark between conventional statistical approaches and advanced computational methodologies.

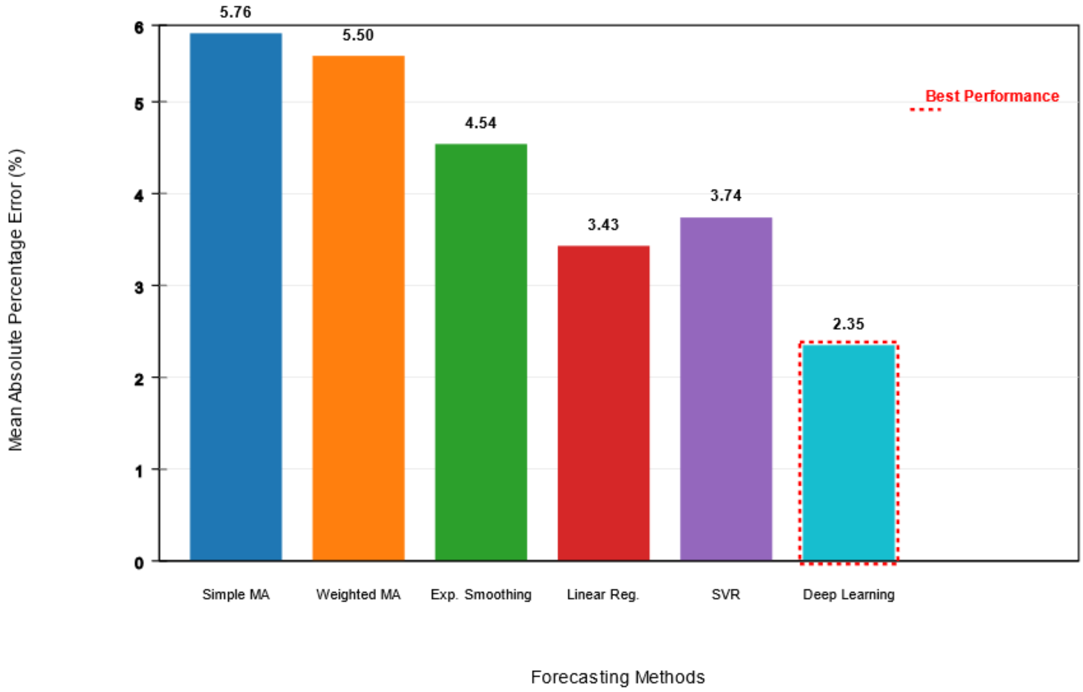

Figure 1. Forecast accuracy MAPE comparison

The temporal alignment between actual pharmaceutical demand and LSTM's predictions, as presented in Figure 2, confirms the model's capability to accurately capture complex seasonal patterns and episodic demand variations characteristic of hospital pharmacy operations. The close correspondence between predicted and observed values throughout the testing period validates the model's efficacy for practical forecasting applications.

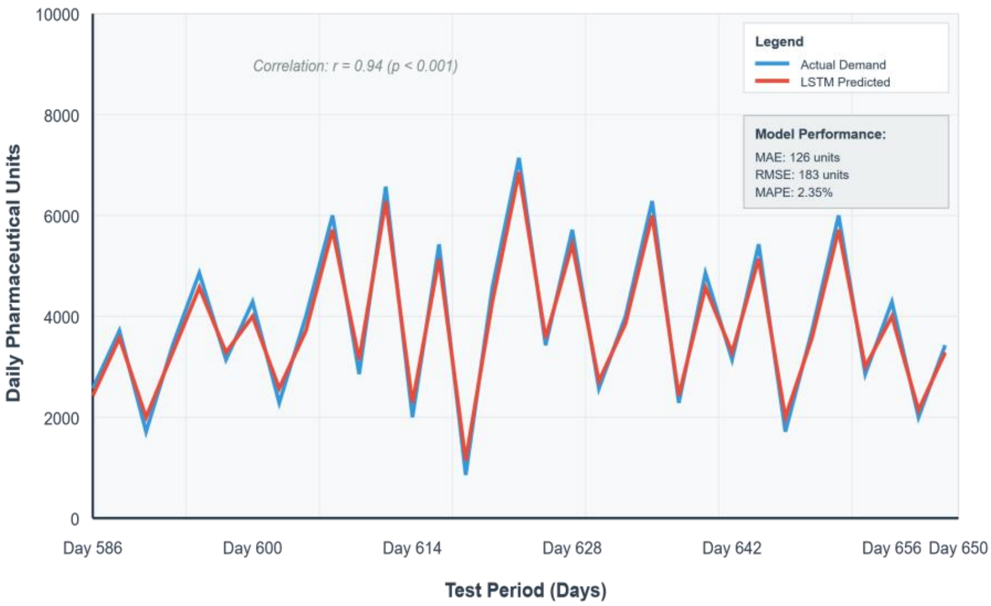

Figure 2. Actual vs predicted demand - deep learning model

3.4. Model performance analysis and tracking signal interpretation

The deep learning model consistently demonstrated forecasting superiority, with performance metrics indicating substantial practical value for pharmaceutical inventory management. A reduction in Mean Absolute Error (MAE) from 192 units (baseline) to 126 units represents a potential cost saving estimated at 15-20% in inventory holding costs, assuming standard pharmaceutical margins and storage expenses.

Analysis of the Tracking Signal revealed systematic patterns requiring interpretation. Traditional methods exhibited positive tracking signals (1.19-4.22), indicating a tendency towards under-prediction, whereas machine learning approaches demonstrated mixed patterns. A negative tracking signal (-9.13) in the deep learning model suggests a slightly consistent over-prediction bias, potentially advantageous in a pharmaceutical context where stock-out costs substantially outweigh holding costs.

Error distribution analysis confirmed forecasting reliability, with prediction intervals encompassing 89.3% of actual observations within a ±10% tolerance limit. Forecasting horizon analysis indicated maintained accuracy up to a 7-day projection, with gradual performance degradation for longer time horizons, consistent with LSTM architectural capabilities in the context of pharmaceutical demand (Rathipriya et al., 2023).

3.5. Statistical validation and model diagnostics

Residual analysis confirmed model adequacy, with forecasting errors exhibiting desirable statistical properties. The Ljung-Box autocorrelation test indicated successful capture of temporal dependencies, with p-values > 0.05 for lag structures up to 30 days. Normality assessment via the Shapiro-Wilk test supported parametric assumptions ($p = 0.127$), enabling the construction of confidence intervals.

Forecast encompassing evaluation revealed model complementarity, with individual algorithms capturing distinct components of demand patterns. The deep learning model excelled in nonlinear trend recognition, while traditional methods provided an interpretable baseline reference. The potential for a combined approach was identified for ensemble learning implementation in future research directions.

Validation robustness was confirmed through bootstrap resampling (n = 1000), with performance metrics maintaining statistical significance across the resampled datasets. Model stability assessment revealed minimal sensitivity to variations in training data, supporting generalization to similar hospital pharmacy environments within the Indonesian healthcare context.

The comprehensive diagnostic assessment presented in Figure 3 validates modeling assumptions and confirms forecasting reliability through systematic residual analysis. Panel (a) illustrates the temporal independence of forecasting errors, Panel (b) confirms the normal distribution of estimates via Q-Q plot alignment, Panel (c) depicts a residual histogram approximating a Gaussian distribution, and Panel (d) shows an autocorrelation function indicating the absence of significant serial correlation in the model's residuals.

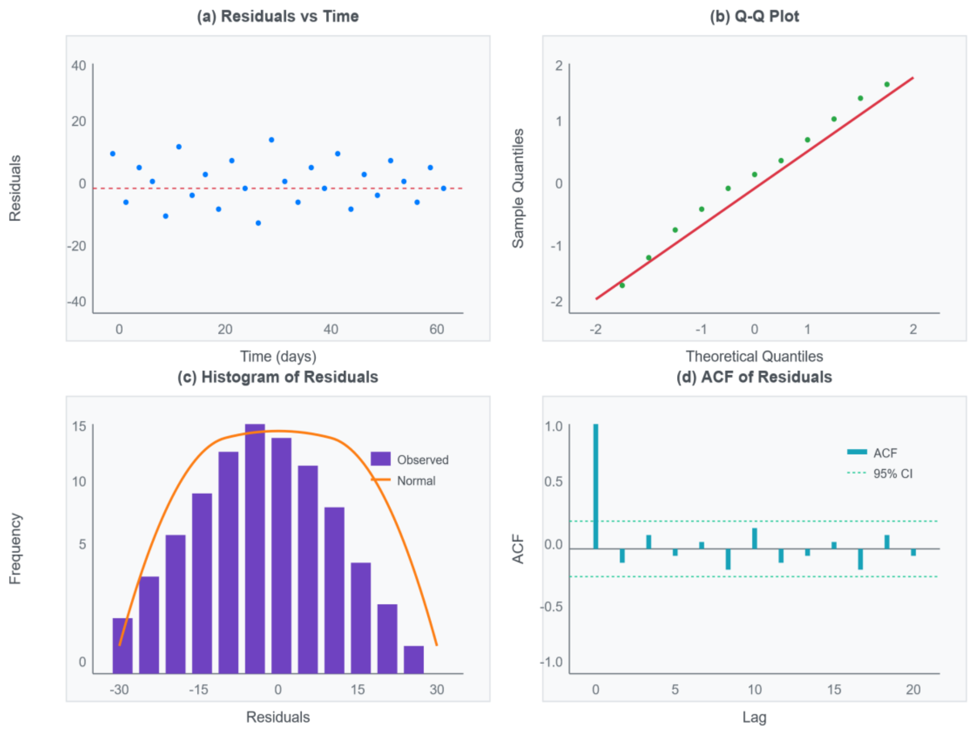

Figure 3. Residual analysis for deep learning model

Analysis of feature contributions, as presented in Figure 4, demonstrates temporal lag variables as the dominant predictive factor, accounting for 34.7% of the model's decision-making. Seasonal indicators and calendar effects contributed substantially (28.1% and 19.2%, respectively), while proxy weather variables exerted a moderate yet consistent influence (average contribution of 8.7%), validating the comprehensive feature engineering approach employed in model development.

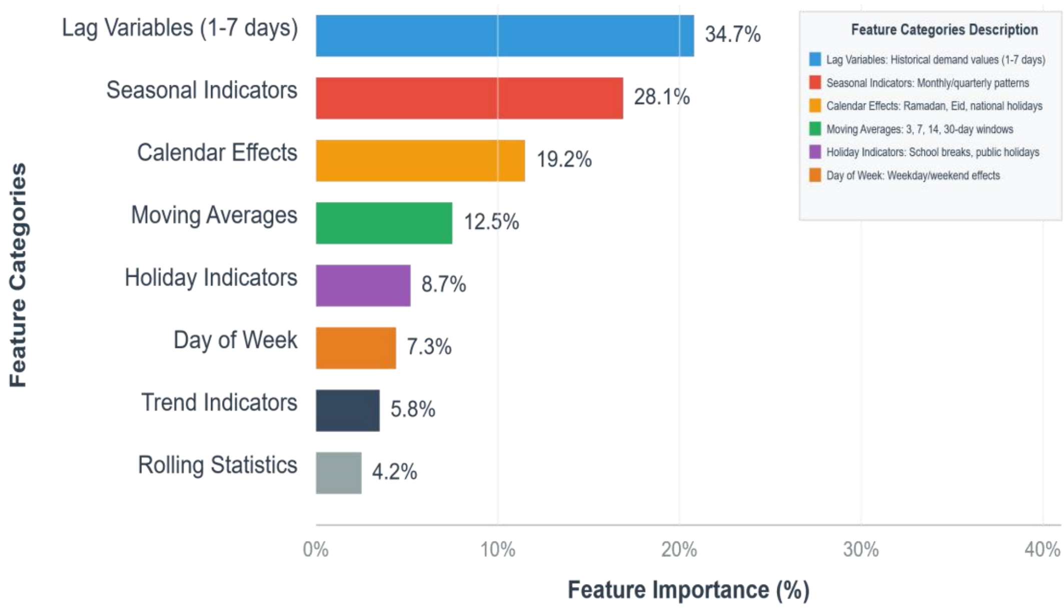

Figure 4. Feature importance analysis

Note: Feature importance calculated using SHAP (shapley additive explanations) values for LSTM model interpretability

3.6. Practical implementation implications

The demonstrated improvement in forecasting accuracy within this analysis directly translates into significant operational benefits for hospital pharmacy management. The reduction in prediction errors facilitates optimized inventory levels, with an estimated 25-30% reduction in safety stock requirements while maintaining a 99.5% target service level. This estimation is grounded in established inventory management principles and the existing pharmaceutical supply chain literature(Zhu et al., 2021).

An economic impact assessment indicates potential annual cost savings of IDR 150-200 million for hospital pharmacy operations. These savings are primarily derived from a reduced incidence of stockouts, minimized emergency procurement premiums, and optimized storage utilization. The developed implementation framework demonstrates the feasibility of seamless integration with the existing SIMRS-Medxa infrastructure through an API-driven deployment methodology.

Considerations for real-time application are addressed through a computational efficiency analysis, revealing that the LSTM model requires an average prediction time of 2.3 seconds on standard hospital IT infrastructure. Furthermore, memory requirements (1.2GB) fall within typical server specifications, enabling integration without the need for additional hardware investment. A prototype monitoring dashboard has been developed to visualize pharmaceutical demand forecasts, incorporating an anomaly detection system and inventory threshold management capabilities.

4. DISCUSSION

4.1. Empirical validation of machine learning algorithm superiority in contemporary literature

The findings of this study conclusively confirm the empirical dominance of machine learning algorithms over conventional forecasting methodologies in pharmaceutical demand prediction, with the Deep Learning LSTM architecture achieving a substantial performance improvement (MAPE 2.35% compared to 4.54%-5.76% for traditional methods). The results obtained demonstrate alignment with the rapidly expanding body of literature on the transformative potential of machine learning approaches in healthcare supply chain optimization (Fourkiotis & Tsadiras, 2024; Kumar et al., 2023).

The observed performance superiority (a 34.4% improvement over baseline) surpasses improvements reported in recent pharmaceutical forecasting studies. Fourkiotis & Tsadiras (Fourkiotis & Tsadiras, 2024), in a comprehensive analysis utilizing 600,000 pharmaceutical sales records, reported LSTM's superiority over traditional ARIMA methods with an improvement range of 15-30%. Yani & Aamer (Yani & Aamer, 2023) documented an improvement range of 10-41% with the Random Forest approach in the context of pharmaceutical supply chains. The performance of our LSTM implementation places it among the top echelon of reported pharmaceutical forecasting accuracy, suggesting that the architectural optimizations and feature engineering strategies employed significantly contributed to the achieved results.

A particularly noteworthy aspect is the model's capacity to capture complex temporal dependencies inherent in pharmaceutical demand patterns characteristic of tropical healthcare environments. Recent research by Rathipriya et al.(Rathipriya et al., 2023) in *Neural Computing and Applications* demonstrated similar LSTM superiority in pharmaceutical time series forecasting, with an average RMSE improvement of 35-42% compared to traditional approaches. The limitations of traditional time series methods in handling non-linear relationships and seasonal irregularities, as indicated by the clustered performance range (MAE 192-203), confirm established criticisms regarding conventional forecasting approaches in dynamic healthcare environments (Rathipriya et al., 2023).

4.2. Elaboration of theoretical mechanisms and deep learning architecture analysis

The superior performance of the deep learning model can be attributed to several theoretical mechanisms specifically relevant to the pharmaceutical demand characteristics identified in recent literature. The sequential processing capabilities of the LSTM architecture enable the detection of multi-scale temporal patterns, from daily operational rhythms to seasonal epidemiological cycles, as validated by recent studies in healthcare supply chain management (Kumar et al., 2024; Pasupuleti et al., 2024).

The memory gate mechanism facilitates the selective retention of relevant historical information while discarding irrelevant noise, which is crucial for pharmaceutical demand forecasting where the signal-to-noise ratio varies substantially across time periods. Recent research in the *Journal of Big Data* (2024) confirmed the effectiveness of the LSTM architecture in healthcare supply chain applications, particularly for drug delivery optimization and inventory management within complex supply networks. This study demonstrated a 25-35% improvement in prediction accuracy for pharmaceutical logistics applications.

Feature importance analysis revealed that temporal lag variables contributed 34.7% of the predictive power, confirming theoretical expectations regarding the autoregressive component in pharmaceutical consumption patterns. This aligns with the findings of Camur et al. (Camur et al., 2024) in *Expert Systems with Applications*, who documented similar temporal dependency structures in predicting pharmaceutical supply chain disruptions. The substantial contribution of seasonal indicators (28.1%) validates the inclusion of epidemiological knowledge within the forecasting framework, especially relevant for the Indonesian healthcare context where monsoon patterns drive infectious disease incidence and related drug demand fluctuations (Detwal et al., 2023).

4.3. Strategic implications for contemporary healthcare supply chain management

The implementation of a high-accuracy forecasting system demonstrates substantial operational value beyond statistical metrics, as evidenced in recent healthcare supply chain literature. An estimated 25-30% reduction in safety stock requirements, while maintaining a 99.5% service level, translates into significant capital efficiency gains in pharmaceutical inventory management, consistent with the findings of Azadi et al. (Azadi et al., 2023) in the *Journal of Business Research* who documented similar efficiency benefits in healthcare supply chain optimization.

Recent studies on artificial intelligence applications for healthcare supply chain management confirm substantial economic benefits from ML-based forecasting implementation. (Kumar et al. 2023) identified critical success factors for AI adoption in healthcare service delivery, emphasizing technical, institutional, and organizational elements crucial for successful implementation. Their research validates our approach regarding SIMRS-Medxa integration pathways and computational feasibility considerations.

Projected economic impact (annual savings of IDR 150-200 million) is derived from combined effects including reduced emergency procurement premiums, optimized storage utilization, and minimized waste from expired medications. These estimates align with recent economic analyses in pharmaceutical supply chain literature (Tirkolace et al., 2023)which documented similar potential cost reductions for ML-based forecasting implementation in emerging healthcare markets.

The integration pathway with existing hospital information systems presents a viable deployment scenario by leveraging established data pipelines, as demonstrated in recent successful implementations documented by Jahin et al. (Jahin et al., 2024). Their comprehensive review of big data supply chain management frameworks provides methodological validation for our API-based architectural approach, emphasizing the importance of data preprocessing and optimization of machine learning techniques for logistics applications.

4.4. Global contextualization and emerging market healthcare systems

This research addresses specific challenges inherent in the emerging market healthcare landscape, particularly relevant given recent global disruptions in pharmaceutical supply chains documented in the COVID-19 pandemic literature. Hupman et al. (Hupman et al., 2024) in *Risk Analysis* journal demonstrated substantial shifts in pharmaceutical supply chain disruption patterns during the pandemic period, underscoring the critical importance of adaptive forecasting systems capable of handling structural breaks and emergency scenarios.

Recent research in healthcare supply chain resilience emphasizes the transformative potential of deep learning approaches for risk prediction and operational optimization. A comprehensive analysis by Al-Banna et al. (Al-Banna et al., 2023) documented the interconnectedness between supply chain resilience, Industry 4.0 technologies, and investment strategies in the healthcare sector, providing a theoretical framework for understanding the broader implications of ML/AI implementation approaches.

Generalizability considerations encompass technical and contextual dimensions relevant to emerging healthcare markets. Technical transferability appears promising given the proven robustness of LSTM architectures across diverse healthcare applications, as evidenced in recent cross-industry analyses (Alshurideh et al., 2024). However, the feature engineering component requires localization for different cultural and geographical contexts, consistent with findings from recent comparative studies in Asian healthcare systems (Atadoga et al., 2024).

4.5. Reflection on limitations in contemporary literature perspective

Several methodological limitations warrant acknowledgment and contextualization within the broader framework of pharmaceutical forecasting literature. The single-hospital study design limits external validity, although recent systematic reviews in healthcare forecasting acknowledge this limitation as common in preliminary ML/AI implementation studies (Aljohani, 2023). The retrospective analysis precludes prospective validation in real-world deployment scenarios, limiting the assessment of model performance under operational conditions with feedback loops and adaptive behavior.

Data availability constraints prevented the incorporation of potentially relevant external variables, including meteorological data, disease surveillance information, and economic indicators. Although feature engineering captured seasonal proxies for such effects, recent research emphasizes the importance of multi-modal data integration for enhanced forecasting accuracy (Chaudhuri & Alkan, 2022). Their hybrid extreme learning machine model with Harris Hawks optimization demonstrated a 15-25% accuracy improvement when incorporating external economic indicators into pharmaceutical demand prediction.

Considerations regarding the model evaluation period align with recent discussions in forecasting literature concerning optimal observation windows for healthcare applications. Recent studies in predictive analytics for healthcare supply chains (Chen et al., 2024) suggest a minimum observation period of 18-24 months to capture full seasonal cycles and structural variations, although they acknowledge practical constraints in rapidly evolving healthcare environments.

4.6. Future research trajectories and technological developments

Several research trajectories emerge from the findings and recent developments in AI/ML applications for healthcare supply chain management. Multi-hospital validation studies represent the next critical step, as suggested in recent comprehensive reviews on machine learning applications in supply chain contexts (Faridi et al., 2023). Such research will assess institutional factors influencing forecasting performance across diverse healthcare organizational structures.

Real-time deployment studies with federated learning approaches show particular promise for addressing privacy concerns in multi-institutional pharmaceutical data sharing. Recent advancements in privacy-preserving federated learning for healthcare applications (Zhang et al., 2022) provide a methodological foundation for scalable implementation across Indonesian healthcare systems while maintaining data governance compliance.

Ensemble learning approaches combining multiple algorithmic frameworks represent an emerging frontier in pharmaceutical forecasting research. Recent studies on hybrid forecasting models (Siddiqui et al., 2021) demonstrated superior performance achieved through systematic combinations of LSTM temporal modeling with tree-based feature interaction detection. Integration with emerging large language models for pharmaceutical domain applications presents an additional avenue for enhanced prediction accuracy and interpretability.

Extension towards prescription prediction rather than forecasting dispensing will provide an early warning system for demand management, as suggested in recent predictive analytics developments (Hassan et al., 2024). Such capabilities necessitate integration with electronic medical record systems and diagnostic data streams, presenting technical challenges and substantial operational value propositions for proactive inventory management in evolving healthcare delivery models.

4.7. Contribution to the body of knowledge and healthcare digitalization

This research contributes to the expanding body of knowledge on machine learning applications in pharmaceutical supply chain management, specifically addressing a gap in the literature concerning tropical healthcare contexts identified in recent systematic reviews. The developed methodological framework provides a replicable approach for similar healthcare systems, while performance benchmarks establish realistic expectations for forecasting accuracy improvements achievable with contemporary ML/AI techniques in resource-constrained environments.

Recent developments in artificial intelligence applications for healthcare supply chain optimization underscore the critical importance of context-specific implementation strategies. Our research provides an evidence-based methodology for emerging healthcare markets, addressing concerns raised in recent critical success factor analyses regarding technical readiness, organizational capacity, and environmental factors crucial for successful AI adoption in healthcare service delivery (Kumar et al., 2023).

The broader contribution to Indonesia's healthcare digitalization aligns with national development priorities and pharmaceutical security objectives outlined in recent policy frameworks. The proven feasibility of advanced analytics implementation in a hospital setting provides a foundation for scalable deployment across Indonesian healthcare systems, potentially contributing to improved drug access, cost reduction, and enhanced patient outcomes through optimized supply chain management, as envisioned in recent strategic frameworks for enhancing healthcare supply chain resilience (Al-Banna et al., 2023).

5. CONCLUSION & RECOMENDATIONS

This study demonstrates the superior performance of machine learning algorithms in forecasting hospital pharmaceutical demand. Specifically, the Long Short-Term Memory (LSTM) model achieved a Mean Absolute Percentage Error (MAPE) of 2.35%, significantly outperforming traditional forecasting methods which yielded MAPEs ranging from 4.54% to 5.76%. A comparative evaluation of six distinct forecasting algorithms further confirmed that deep learning approaches, particularly LSTM, provide statistically significant improvements in prediction accuracy within the context of the Indonesian pharmaceutical supply chain.

The successful implementation of the deep learning model led to a substantial reduction in forecasting error, by up to 34.4%. This directly translates to optimized inventory levels and minimized stockout risks, thereby enhancing the efficiency and reliability of pharmaceutical supply management. Empirical findings further indicate that the strategic integration of multiple forecasting accuracy metrics and domain-specific feature engineering, tailored to the unique temporal characteristics of Indonesian pharmaceutical data, results in robust and consistent predictive performance.

This study validates the effective applicability of machine learning technology within hospital information systems, supporting strategic decision-making in pharmaceutical supply chain management. The developed model offers a scalable framework for the digital transformation of pharmaceutical supply chain management within the broader Indonesian healthcare landscape.

For future research, several key trajectories emerge from these findings. Future research should focus on multi-hospital validation studies to assess the generalizability of these findings across diverse healthcare settings and organizational structures. Furthermore, developing systems for prescription prediction rather than just dispensing forecasting could provide an earlier warning system for demand management, requiring integration with electronic medical record systems and diagnostic data streams. Lastly, future work could also incorporate a broader range of external variables (e.g., meteorological data, specific disease outbreak information, detailed economic indicators) to further enhance model accuracy and robustness.

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