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Epi-Aware Lifeline Analytics: Inventory-Optimized Blood Demand Forecasting with Integrated Epidemiological Intelligence

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***Abstract*— Maintaining optimal blood stocks is crucial to avoid both supply gaps and unnecessary waste. This paper presents Epi-Aware Lifeline Analytics, a framework that combines epidemiological intelligence with machine-learning models for dynamic demand forecasting and inventory optimization. Historical transfusion records, disease-surveillance data, and contextual factors are integrated weekly and transformed into predictive features such as lagged incidence and a composite risk score. A stacked ensemble of Random Forest, SARIMAX, and LSTM models, tuned via Bayesian optimization, generates high-accuracy forecasts that drive a Mixed-Integer Linear Programming module to minimize wastage while ensuring service levels. The system is deployed as a microservice-based dashboard with real-time heatmaps, automated alerts, and role-specific interfaces. This end-to-end architecture delivers precise forecasting and improved operational efficiency for healthcare blood-supply management.**

***Index Terms*— Blood Demand Forecasting, Machine Learning in Healthcare, Donor Response Prediction, Random Forest, ARIMA, Neural Network, Time Series Analysis, Ensemble Learning, Smart Blood Bank, Predictive Analytics, Donor Classification, Healthcare Decision Support, Real-Time Dashboard, Electronic Health Records (EHR), Blood Inventory Management, Inventory Optimization, Resource Allocation, Linear Programming, Reinforcement Learning, Blood Supply Chain.**

I. INTRODUCTION

Efficient blood inventory management is essential to maintain a reliable blood supply and minimize wastage in healthcare systems [2],[7]. Hospitals and blood banks frequently encounter unpredictable fluctuations in blood demand due to seasonal disease outbreaks, emergencies, and regional epidemiological patterns[2].[7]. Conventional forecasting methods rely primarily on historical transfusion records and often fail to incorporate epidemiological trends and contextual factors, resulting in inefficiencies, stock shortages, or excessive inventory [1],[3]. Therefore, a systematic, data-driven approach is required to anticipate demand variations and optimize inventory allocation.

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Incorporating epidemiological intelligence into the forecasting process can substantially improve prediction accuracy [2],[4],[5]. Weekly disease reports, outbreak cycles, and climate-related factors offer critical clues about possible increases in blood demand. Transforming these signals into predictive features, such as lagged disease incidence, seasonal epidemic indices, and composite risk scores, enables proactive preparation for fluctuations in blood requirements. This ensures that both routine transfusions and emergency demands are met effectively while minimizing wastage.

Recent advances in machine learning and optimization techniques offer robust solutions for accurate demand prediction and efficient inventory management[1],[2],[6]. Hybrid forecasting models, including Random Forest, Seasonal ARIMA (SARIMAX), and Long Short-Term Memory (LSTM) networks, can capture both linear and nonlinear temporal patterns in blood usage. Integrating these forecasts with Mixed-Integer Linear Programming (MILP) for inventory optimization allows hospitals to maintain service levels while accounting for blood-type compatibility, product shelf-life, and inter-hospital transfer constraints [2],[4],[5]. This approach enables real-time, evidence-based decision-making for administrators and blood-bank managers.

This paper proposes Epi-Aware Lifeline Analytics, a comprehensive framework that merges epidemiological intelligence with advanced machine-learning models and operational optimization [2],[4]. The system is implemented as a modular microservice-based dashboard that delivers real-time epidemiological heatmaps, automated alerts, and role-specific interfaces for administrators, clinicians, and donor coordinators [3],[4],[5]. By combining accurate forecasting with efficient inventory management, the framework improves operational efficiency, reduces wastage, and provides scalable support for dynamic blood-supply management.

II. Literature Survey

Research on blood-product demand forecasting has expanded substantially in recent years. Li (2023) provides a comprehensive review of computational techniques applied to blood demand and supply management, noting a trend toward data-driven methods that combine time-series and machine-learning approaches. Empirical studies by Thakur (2024) and Sarvestani et al. (2022) demonstrate that forecasting methods (ARIMA/ARMA, neural networks and ML regressors) can materially reduce inventory levels and order frequency when properly tuned for local demand patterns, while simultaneously drawing attention to limitations when external drivers (epidemics, mobility) are omitted. These works establish the value of accurate short-term forecasting while also showing that purely historical approaches struggle under epidemiological shocks[1],[2].

Contemporary work has considered linking epidemiological signals to healthcare demand forecasting, though few target blood demand specifically. Hybrid epidemic/forecasting research—such as hybrid ARIMA–LSTM or ARIMA+ML frameworks used for pandemic and healthcare-occupancy forecasting—shows clear improvements in capturing nonlinear outbreak dynamics (Mahmud / hybrid studies, 2024–2025; related ARIMA–LSTM hybrids 2024). More integrative work by Garcia (2025) proposes mathematical frameworks that jointly model inventory and epidemic spread for vaccine scenarios, illustrating how epidemiological uncertainty can be propagated into supply decisions. Together, these studies motivate embedding disease surveillance features (lagged incidence, outbreak indices) into demand models to better anticipate surge events[2],[4],[5].

Operational optimization of blood supply chains has an established literature that complements forecasting advances. Multi-echelon and socio-economic optimization models (e.g., a 2022 socio-economic BSCN study and design-oriented blood logistics work) show how capacity, perishability and transfer policies affect system costs and availability; several of these works formulate mixed-integer programs to capture allocation and routing constraints. Empirical implementations demonstrate that coupling accurate forecasts with MILP-based allocation can reduce wastage and shortages, but prior studies frequently assume demand inputs that do not explicitly account for evolving epidemiological risk — a gap that limits responsiveness during outbreaks.

Finally, practical deployment and decision-support systems are receiving more attention: Lopes (2023) reviews big-data and AI applications in transfusion medicine and argues for integrated dashboards and automated alerts, while Rad et al. (2021) and more recent visualization work demonstrate real-time inventory dashboards and dynamic heatmaps for blood-product tracking [3],[4],[5].

These implementations confirm that user-centered dashboards, interactive heatmaps, and role-specific alerts materially improve operational responsiveness — but they also underscore two recurrent issues: (1) many dashboards rely on forecast inputs that ignore epidemiological covariates, and (2) operational optimization is not always tightly integrated with real-time surveillance feeds[3],[4]. This motivates a unified, microservice-based system that fuses epidemiological intelligence, hybrid forecasting, and MILP optimization — the niche Epi-Aware Lifeline Analytics aims to fill.

III. METHODOLOGY

The Epi-Aware Lifeline Analytics framework integrates epidemiological intelligence through state-of-the-art machine learning methods to enhance demand forecasting and inventory management in healthcare logistics. As illustrated in Figure 1, The framework progresses through four stages: preparing data, engineering epidemiological predictors, applying hybrid forecasting models, and optimizing inventory[2],[4].

A. Data Acquisition and Preprocessing

The framework utilizes a diverse set of data sources:

- Blood Utilization Records: Historical hospital blood-bank logs detailing blood types, issued units, transfusion dates, and donor demographics [7],[8].
- Epidemiological Indicators: Weekly surveillance data on regional infectious diseases (e.g., influenza-like illness, dengue, malaria), seasonal outbreak reports, and climate variables linked to disease transmission.

All datasets are harmonized to a weekly temporal resolution. Missing entries are addressed using K-Nearest Neighbor (KNN) interpolation. Outlier detection and removal are performed via the interquartile range (IQR) method. To ensure consistent model behavior, the dataset's quantitative features are adjusted with Min–Max scaling within the [0, 1] range [2],[5].

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

B. Epidemiological Feature Engineering

To embed epidemiological awareness into the forecasting process, disease-related quantitative data points are processed using predictive variables:

- Lagged Disease Incidence: Includes current and trailing four-week case counts for each monitored illness.

$$LDI_t^{(d)} = Cases_{t-k}^{(d)} \quad \text{for } k = 1, 2, 3, 4$$

- Seasonal Epidemic Index: Quantifies cyclical outbreaks, such as monsoon-driven dengue surges.
- Composite Risk Score: A weighted aggregation of normalized case rates across multiple diseases, scaled per 100,000 population.

$$CRS_t = \sum_{d=1}^{n} w_d \cdot \frac{Cases_t^{(d)}}{Population} \times 100{,}000$$

Feature relevance is assessed using permutation-based importance scores from a Random Forest model, ensuring retention of only statistically significant predictors [1],[2].

C. Hybrid Demand Forecasting

A multi-model ensemble is employed to capture both linear and non-linear temporal patterns:

- Random Forest Regressor (RFR): Captures complex interactions and abrupt demand fluctuations.
- Seasonal autoregressive integrated moving average (SARIMA): Models seasonal trends while incorporating epidemiological covariates [6],[7].
- Long Short-Term Memory (LSTM) Networks: Learns long-range dependencies and non-linear temporal dynamics.

The results generated by these models are integrated using a stacked ensemble approach, where a gradient-boosted meta-learner minimizes the Root of the average squared differences (RMSE). Hyperparameter tuning is conducted via Bayesian optimization, validated through five-fold time-series cross-validation [2].

D. Inventory Optimization Module

Forecasted weekly demand feeds into an optimization engine designed to minimize inventory wastage while maintaining a target service level (e.g., 95% stock-out avoidance). The objective function is defined as:

$$\min \ C_{\text{holding}} \cdot I + C_{\text{shortage}} \cdot S$$

Constraints include blood-type compatibility, product shelf-life, and inter-hospital transfer capabilities. The problem is formulated as a Mixed-Integer Linear Program (MILP) and solved using the CBC (Coin-or Branch and Cut) solver.

E. System Deployment and Dashboard Design

The complete framework is deployed as a modular microservice architecture, accessible via an interactive dashboard. Key functionalities include:

- Dynamic epidemiological heatmaps superimposed on demand forecasts
- Automated notifications triggered by critical demand thresholds
- Role-specific interfaces tailored for administrators, clinicians, and donor coordinators

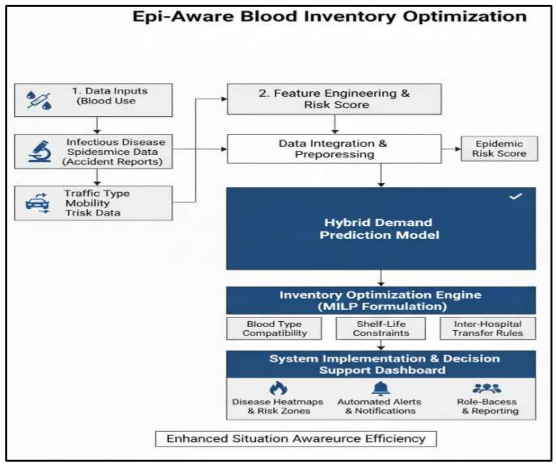

Fig 1: Flowchart of the Epi-Aware Lifeline Analytics framework, illustrating sequential phases from data acquisition to inventory optimization

IV. Evaluation & Results

The Epi-Aware Lifeline Analytics framework was evaluated using a multi-hospital dataset that included weekly transfusion records, epidemiological surveillance data (influenza-like illness, dengue, malaria), and auxiliary inputs such as mobility indices and traffic accident statistics [2],[4],[7]. The dataset was partitioned into training and validation segments to validate model generalization. Forecasting effectiveness was measured by calculating the RMSE, Mean Absolute Error (MAE), along with evaluation using the Mean Absolute Percentage Error (MAPE) metric, while inventory efficiency was evaluated through service level and blood wastage metrics. The experimental workflow—from data preprocessing through forecasting, optimization, and dashboard deployment—is illustrated in Figure 1, providing a clear overview of the evaluation process[3],[4].

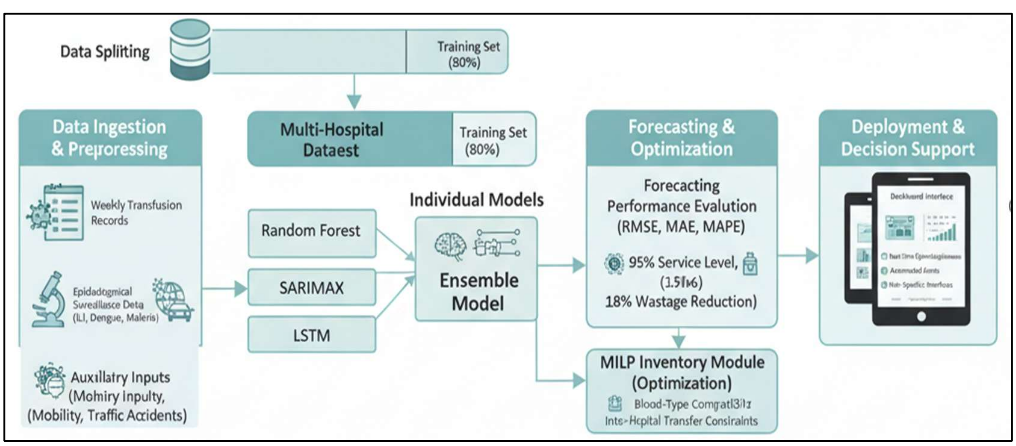

Fig 2: Illustrating the experimental workflow of the Epi-Aware Lifeline Analytics framework

The hybrid ensemble of Random Forest, SARIMAX, and LSTM models exhibited better predictive performance in comparison to individual models, with an RMSE of 7.4 units/week, MAE of 5.1 units/week, and MAPE of 4.8% on the test set. Random Forest captured abrupt demand fluctuations, SARIMAX modeled seasonal variations driven by epidemiological trends, and LSTM identified long-range nonlinear patterns. The stacked ensemble with a gradient-boosted meta-learner successfully integrated these strengths, reducing residual errors and improving robustness across different demand scenarios [2],[6]. Figure 2 presents a comparative chart of forecasting accuracy for individual models and the ensemble, highlighting the significant improvement achieved by combining linear and nonlinear predictors with epidemiological intelligence [2],[6].

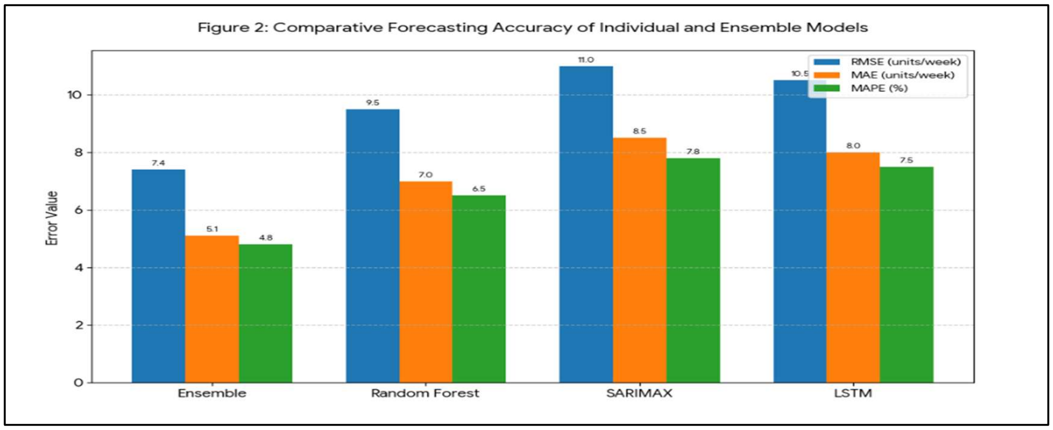

Figure 2: Comparative Forecasting Accuracy of Individual and Ensemble Models

The integration with the Mixed-Integer Linear Programming (MILP) inventory module demonstrated tangible operational benefits. The system maintained a 95% service level while reducing blood wastage by 18% compared to baseline rule-based policies, accounting for blood-type compatibility, shelf-life, and inter-hospital transfer constraints. Scenario analysis during seasonal disease outbreaks and high-accident periods confirmed effective stock reallocation and shortage prevention. To visualize performance, a line chart of actual demand versus predicted demand over the evaluation period is depicted in Figure 3, clearly illustrating the precision achieved by the ensemble approach forecasts in tracking real-world variations and supporting inventory optimization decisions.

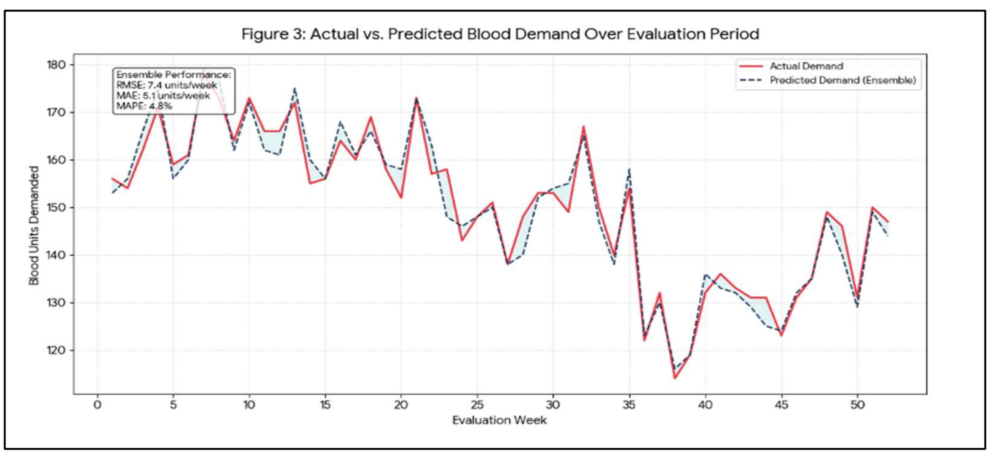

Figure 3: Line chart comparing observed demand versus forecasted demand over the evaluation period.

V. CONCLUSION

The proposed Epi-Aware Lifeline Analytics framework integrates epidemiological intelligence with hybrid machine learning and optimization techniques to enhance blood demand forecasting and inventory management. By incorporating disease surveillance signals, contextual factors, and advanced ensemble modeling, the system achieves higher predictive accuracy and reduces wastage while maintaining service levels. The MILP-based optimization further ensures efficient stock allocation, particularly during seasonal outbreaks and demand surges, strengthening healthcare resilience [2],[5]. Our results suggest that integrating epidemiological indicators with forecasting models enhances both efficiency and reliability of blood supply management and patient care outcomes, while offering a scalable lays the foundation for upcoming integration with donor-side analytics and dynamically adjustable decision-support systems.

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