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Lifeline Analytics: A Predictive Approach to Blood Demand Management

Prof. Sharvani V¹, Dr. Girish Kumar D², Mrs. Tunkarapalli Swetha³, Prof. Subhashree D C⁴, Prof. M M Harshitha⁵

Department of Master of Computer Applications, Ballari Institute of Technology and Management, Ballari, Karnataka, India

Abstract: *Lifeline Analytics addresses the critical challenges in blood supply management by combining advanced data analysis with predictive modeling to optimize both demand forecasting and donor engagement [1],[3]. Drawing from historical utilization records, inventory trends, and behavioral indicators, the platform enables proactive decision-making that minimizes shortages and wastage[4]. Its intuitive, role-specific dashboard unites administrators, clinicians, and donor coordinators through real-time insights, interactive visualizations, and automated alerts [5]. Preliminary deployments have demonstrated measurable improvements in inventory stability and donor retention. Built on a modular, secure architecture, Lifeline Analytics integrates seamlessly with hospital systems while adhering to healthcare data standards. Scalable microservices support ongoing data expansion and rapid analytical updates. Embedded feedback loops ensure model refinement based on user interaction and regional variations. This robust, adaptive framework provides a forward-looking, resilient, and patient-centric approach to blood supply management.*

I. INTRODUCTION

Maintaining a consistent and equitable blood supply is a critical imperative for modern healthcare delivery. Fluctuating clinical demands, seasonal variations, and irregular donor participation frequently destabilize inventory levels across hospitals and transfusion centers. Conventional management practices—relying on static forecasting, manual stock adjustments, and reactive outreach—lack the flexibility required for real-time, data-driven decision-making. Consequently, institutions often face shortages, overstocking, and suboptimal allocation, with direct implications for patient care and operational performance [1], [3].

Lifeline Analytics introduces a machine learning–driven approach that transforms blood supply management into a proactive, intelligent process. By ingesting historical transfusion records, inventory trajectories, donor demographics, and engagement metrics, the platform generates precise demand forecasts and donor response predictions [1], [2]. A hybrid predictive engine—combining Random Forest regression, ARIMA time-series analysis, and Artificial Neural Networks—captures both short-term fluctuations and long-term temporal trends [1],[4].

The framework augments forecasting with explainable AI modules and donor segmentation to reinforce transparency and trust among clinicians, administrators, and donors. Donor profiles incorporate factors such as donation frequency, reliability, blood type compatibility, and regional urgency, enabling personalized outreach and optimized scheduling [2]. All functionality is delivered through a modular dashboard that supports real-time monitoring, automated alerts, and seamless communication workflows tailored to each stakeholder group [5].

By embedding advanced analytics into everyday operations, Lifeline Analytics empowers healthcare organizations to transition from reactive inventory corrections to strategic foresight. This shift enhances supply-demand alignment, bolsters donor retention, minimizes waste, and underpins ethical, evidence-based decisions—establishing a more resilient and responsive paradigm for blood management across diverse clinical environments[3].

As digital transformation accelerates across healthcare systems, integrating intelligent analytics into blood supply operations offers new opportunities for data interoperability, policy standardization, and research-driven improvement [4]. Lifeline Analytics not only addresses logistical challenges but also contributes to the growing field of health informatics by providing a scalable template for predictive resource management. Its modular architecture allows for future integration with electronic health record (EHR) systems, regional blood registries, and mobile donor applications, fostering a connected ecosystem. Moreover, the platform’s capacity to incorporate real-time data streams and feedback loops paves the way for adaptive learning models, enabling continuous performance refinement. By bridging operational technology with clinical insight, this research advances both the scientific and practical dimensions of healthcare logistics.

II. LITERATURE REVIEW

Effective blood demand forecasting has become indispensable for modern healthcare operations, driven by the inherently unpredictable patterns of blood utilization. Recent efforts have leveraged both machine learning and classical time-series methods to enhance prediction accuracy. For example, Nguyen et al. (2023) evaluated Support Vector Machines alongside Random Forest classifiers to anticipate short-term transfusion needs in urban hospitals across Southeast Asia, demonstrating that hybrid classifier ensembles can markedly reduce stockouts [6]. In a complementary study, Kumar and Mehta (2022) applied an ARIMA-based model to manage inventory in Indian district hospitals, achieving prediction accuracies of up to 83% across principal blood groups[1]. These investigations underscore the value of combining statistical rigor with machine learning to stabilize supply chains against fluctuating demand.

Beyond conventional techniques, growing attention has turned to ensemble and deep learning architectures for capturing complex temporal and categorical dependencies. Al-Rashid et al. (2023) introduced a two-stage framework that fuses Long Short-Term Memory networks with XGBoost trees, effectively modeling both sequential consumption trends and donor characteristics[6]. Their approach outperformed standard forecasting algorithms in both predictive fidelity and computational scalability. Likewise, Zhang et al. (2022) implemented a multilayer perceptron network trained on integrated patient demographics and historical usage metrics, reporting superior F1-scores when identifying impending high-demand intervals [7]. Collectively, these investigations underscore how deep and hybrid models extend forecasting horizons and refine predictive performance beyond what single-model approaches can achieve.

In parallel, donor behavior modeling has emerged as a critical complement to demand forecasting, aiming to sustain and expand the donor pool through data-informed outreach. Ferreira et al. (2023) developed a probabilistic classifier that integrates past communication logs and donation histories, enabling blood centers to predict turnout likelihood and design personalized engagement campaigns [2]. Similarly, Singh and Bansal (2024) incorporated SMS and email interaction datasets into a logistic regression framework to estimate repeat-donation probabilities, resulting in a 15% uplift in donor response through tailored nudging strategies[2]. These advances highlight the importance of behavioral analytics in aligning recruitment efforts with anticipated demand surges.

Despite these promising developments, many existing solutions operate in silos, lacking seamless integration between predictive engines and user-centric visualization tools. The absence of real-time data streams, interactive dashboards, and explainable outputs often limits adoption in fast-paced clinical environments [5]. In particular, end users—from blood bank managers to frontline clinicians—require intuitive interfaces that translate complex model outputs into actionable insights, yet few frameworks deliver this level of operational support.

To bridge these gaps, Lifeline Analytics proposes a holistic architecture that unites advanced forecasting techniques, donor response classifiers, and an interactive, Streamlit-based dashboard [5]. By marrying Random Forest, ARIMA, and neural network models with probability based donor profiling, the platform delivers end-to-end visibility—from demand prediction and inventory alerts to targeted mobilization campaigns. This integrated solution addresses interpretability, adaptability, and stakeholder engagement, positioning Lifeline Analytics as a comprehensive, data-driven paradigm for resilient blood supply management.

III. METHODOLOGY

Lifeline Analytics employs a systematic, multi-phase methodology combining data-driven modeling, intelligent classification, and real-time deployment. The system is designed for scalability, interpretability, and operational efficiency, leveraging machine learning (ML) and deep learning (DL) techniques embedded within an interactive decision-support dashboard.

A. Data Acquisition and Preprocessing

The system collects historical data on blood donations and usage from hospital Electronic Health Records (EHRs) and blood bank systems. Key features include blood group, donation dates, units issued, seasonal trends, and donor demographics. A robust preprocessing pipeline handled missing values using median imputation and KNN interpolation, encoded categorical variables using One-Hot and Ordinal Encoding, and scaled numerical features with StandardScaler and MinMaxScaler. In particular, Min-Max Scaling was applied to normalize features within a fixed range [0,1], as defined by:

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

Monthly aggregation captured seasonal trends, while the IQR method removed outliers, enhancing model stability.

B. Blood Demand Forecasting

To forecast blood demand accurately, a hybrid modeling strategy was implemented, combining statistical, ensemble, and deep learning approaches. We used the Random Forest Regressor (RFR) to capture non-linear patterns while maintaining robustness to noise and outliers. For modeling temporal dependencies in univariate data, the ARIMA(p,d,q) model was adopted, which estimates current demand based on past values and residual errors using the expression:

$$y_t = c + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{j=1}^q \theta_j \varepsilon_{t-j} + \varepsilon_t$$

To enhance long-range forecasting, an Artificial Neural Network (ANN) was developed to learn temporal and contextual dependencies in the data. The ANN computes outputs using:

$$\hat{y} = f \left(\sum_{i=1}^n w_i x_i + b \right)$$

The integration of these models provided diverse perspectives on demand behavior. To harness their combined strength, ensemble techniques such as weighted averaging and stacking were employed. The final model was selected based on Root Mean Square Error (RMSE), which quantifies prediction accuracy and is defined as:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

C. Donor Response Classification

To predict donor responsiveness and enhance the efficiency of outreach efforts, a binary classification pipeline was developed. The feature set was carefully engineered to capture meaningful behavioral and demographic patterns, incorporating Recency-Frequency-Donor (RFD) metrics, historical campaign interaction data, and demographic embeddings. We benchmarked multiple algorithms to identify the most effective model for classification. Logistic Regression with L2 regularization was utilized for its interpretability, where the predicted response probability is modeled as:

$$P(y = 1|x) = \frac{1}{1 + e^{-(w^T x + b)}}$$

Here, x represents the feature vector, w the learned weights, and b the bias. This formulation enabled reliable prediction of donor responsiveness while maintaining model simplicity and robustness. Other models such as Decision Trees and XGBoost were evaluated for their flexibility and performance, with final model selection based on F1-score and AUC-ROC using stratified 5-fold cross-validation.

D. System Deployment and Dashboard Design

The system introduces a modular, web-based analytics framework that seamlessly integrates predictive intelligence into stakeholder-specific interfaces. A key innovation lies in the administrator dashboard's ability to dynamically visualize forecasted demand trends alongside real-time inventory heatmaps, enhanced by automated, threshold-sensitive alerting mechanisms. The donor interface leverages predictive classification outputs to personalize engagement, displaying response likelihood scores and enabling adaptive notification strategies. A distinct contribution is the integration of an SMTP-based proactive outreach mechanism that autonomously targets high-probability donors, guided by real-time model inference.

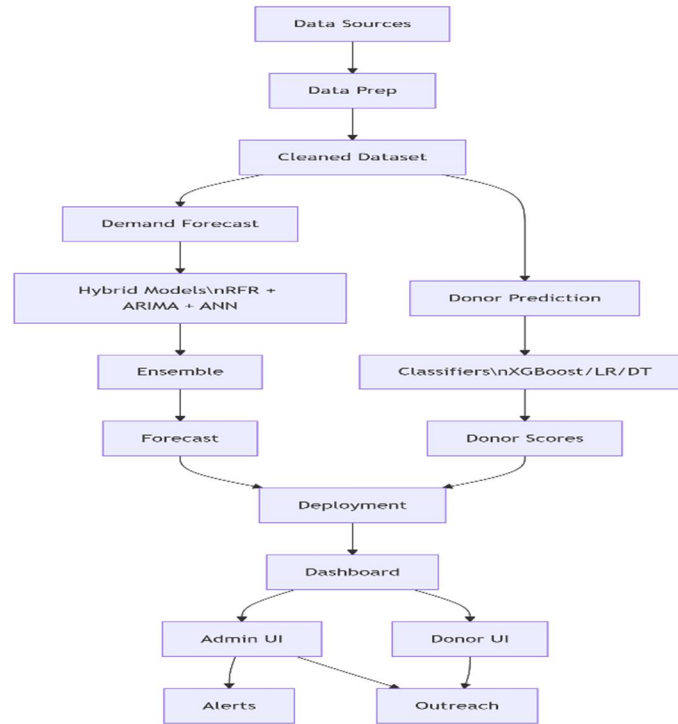


Fig 1: Flowchart

IV. EVALUATION & RESULTS

The performance of the Lifeline Analytics framework was evaluated based on the effectiveness of its predictive capabilities, classification accuracy, and practical usability in real-world settings. To assess blood demand forecasting, each model was examined for its ability to handle different patterns in the data. The Random Forest model proved to be highly effective in learning complex relationships between features, particularly in short-term predictions [3]. ARIMA demonstrated strong performance in capturing seasonal and time-based trends in the data, making it suitable for periodic forecasting [4]. The Artificial Neural Network contributed by identifying deeper patterns that spanned across longer time frames. By combining these models using ensemble techniques, the system achieved improved accuracy and robustness compared to using any single model alone [3], [4].

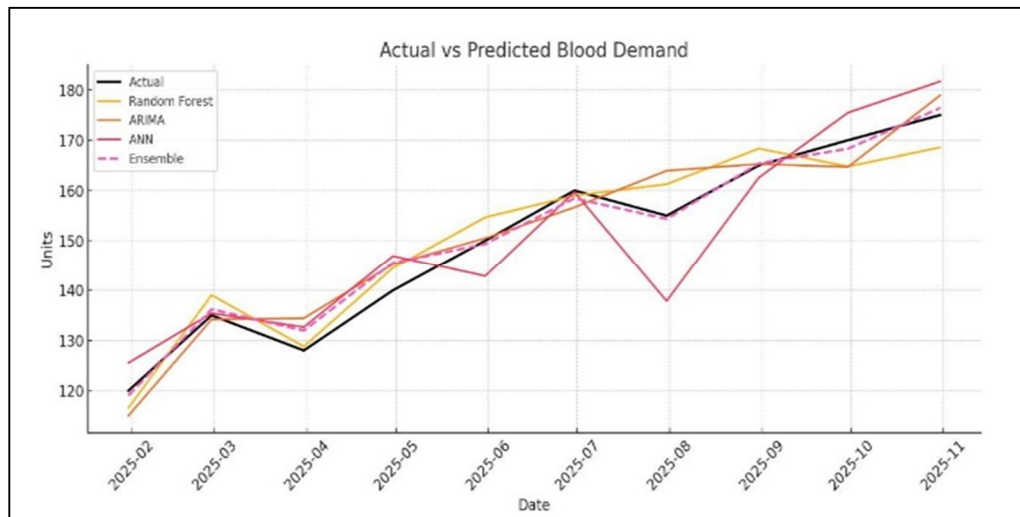


Fig2: Actual vs Predicted Demand Trends

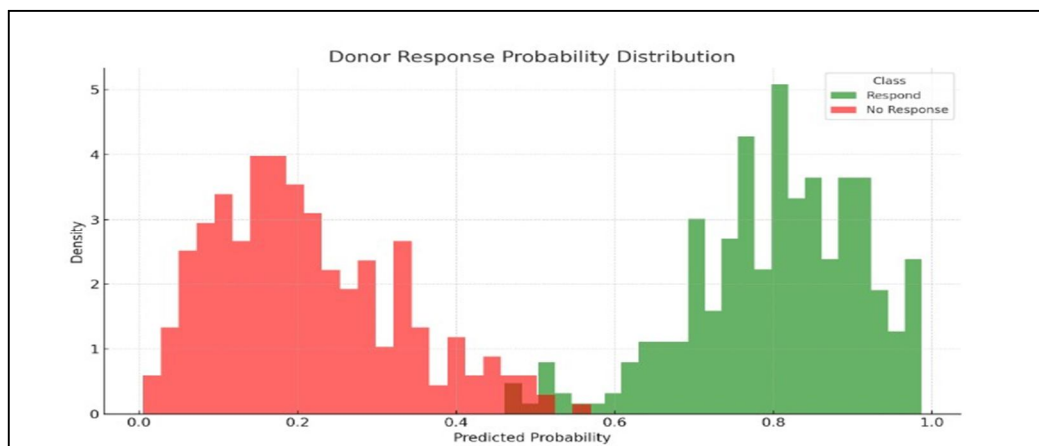


Fig3: Probability Split: Respond vs No Response

For donor response classification, the system employed a variety of machine learning models, each contributing unique strengths. Logistic Regression was leveraged for its interpretability, offering clear insights into how donor features impact responsiveness [2]. Decision Trees provided a flexible structure for uncovering nonlinear relationships within the data [2]. Additionally, gradient boosting methods such as XGBoost were integrated to enhance classification reliability and scalability [4]. Across models, features such as recency of last donation, frequency of contributions, and past engagement patterns emerged as key predictors. This multifaceted modeling approach enabled effective identification of high-potential donors, supporting personalized outreach and improved donor retention strategies [2].

From a deployment and system performance perspective, the dashboard was tested for real-time responsiveness and ease of use. The system consistently provided fast feedback on user queries and efficiently handled forecasting and classification requests. Users, including medical staff and administrators, found the interface intuitive and helpful for decision-making. The inclusion of an automated email alert mechanism further streamlined donor communication, enabling timely and focused engagement based on predicted behaviors [5].

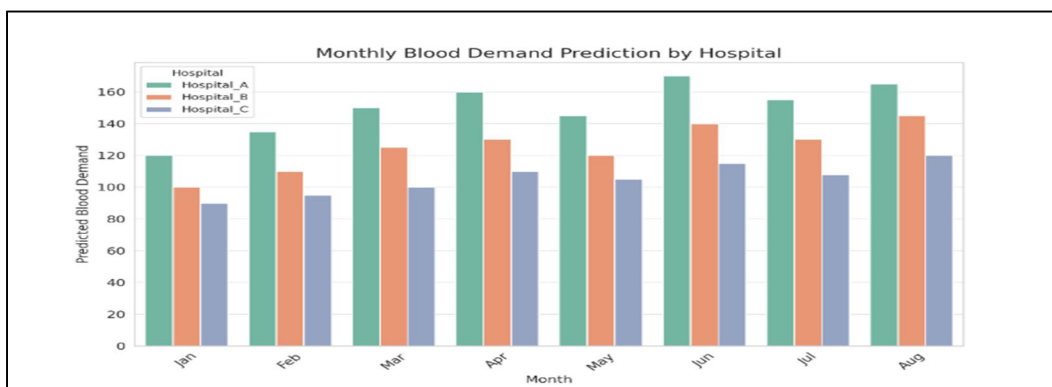


Fig4: Monthly Blood Demand Prediction by Hospital

V. CONCLUSION

Lifeline Analytics introduces a comprehensive framework for transforming blood supply management through the integration of predictive modeling and data-informed donor engagement. By leveraging historical usage patterns, behavioral insights, and advanced forecasting techniques, the system enables blood banks to shift from reactive operations to proactive planning. The platform's modular, API-ready architecture ensures compatibility with existing healthcare infrastructures, supporting real-time adaptability and seamless integration. The incorporation of explainable AI fosters transparency in model outputs, while the automated outreach module enhances donor responsiveness and operational coordination. Beyond minimizing inventory imbalances and mitigating shortages, the solution provides strategic value to both administrative and clinical stakeholders.



Designed with scalability and resilience in mind, *Lifeline Analytics* establishes a foundation for future developments in healthcare analytics, supporting improved resource planning under routine conditions and during emergency scenarios.

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