Intelligent Blood Supply Management

Demand Forecasting and Donor Segmentation for Inventory Optimization

Team IDGAF | Section A & B

Role	Name	Roll No
Leader	Jasleen	10045
Member	Manasvi	10406
Member	Akshat	10060
Member	Ankita	10062
Member	Antara	10106

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1. Problem Background & Motivation

1.1 The Blood Supply Challenge

Blood transfusion is a life-saving medical intervention with no synthetic substitute. Blood banks worldwide face a fundamental operational dilemma:

The Dual Challenge: - **Shortage Risk**: Unpredictable demand spikes (accidents, surgeries, emergencies) combined with variable donor availability can lead to critical shortages, directly impacting patient outcomes and potentially causing loss of life. - **Wastage Risk**: Blood components are perishable—platelets expire in just 5 days, packed red blood cells in 42 days. Overstocking leads to expensive wastage of a precious, donated resource.

1.2 Scale of the Problem

According to the **2019 National Blood Collection and Utilization Survey (NBCUS)**: - **13.02 million** donors presented for donation in the US - **10.8 million** RBC units were transfused to **4.2 million** recipients - Wastage rates range from **5-15%** depending on component and facility - Young donor participation (16-24 years) declined by 10.1% - Donors 65+ increased by 10.5%, raising sustainability concerns

The **Nepal BPKIHS study (2023)** documented **7.13% overall wastage** with **92.9% utilization**, establishing a benchmark for inventory performance. Platelet concentrates showed the highest wastage rates due to their short shelf life.

1.3 Project Objectives

Objective	Target Metric
Demand Forecasting	MAPE < 20%
Donor Segmentation	Silhouette Score > 0.35
Inventory Optimization	Actionable recommendations

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2. Dataset Description

2.1 Data Sources

Dataset	Records	Type	Source
UCI Blood Transfusion	748	Real	UCI ML Repository
Synthetic Donor Registry	10,000	Synthetic	NBCUS 2019 statistics
Demand Time-Series	4,380	Synthetic	3 years daily data
Supply/Inventory	4,380	Synthetic	Nepal BPKIHS study

2.2 UCI Blood Transfusion Dataset (Real Data)

Feature	Description	Range
Recency	Months since last donation	0.03 - 74.4
Frequency	Total number of donations	1 - 50
Monetary	Total blood donated (cc)	250 - 12,500
Time	Months since first donation	2.27 - 98.3
Donated	Target variable	Binary (24% positive)

2.3 Synthetic Data Generation

Based on real-world statistics: - **Blood types**: WHO distribution (O+: 37%, A+: 28%, B+: 20%, O-: 6%) - **Demographics**: NBCUS 2019 (30% first-time, 70% repeat donors; 54% male) - **Deferrals**: 15% rate (top reason: low hemoglobin at 43%) - **Demand patterns**: Weekly seasonality, winter peaks, holiday spikes, random emergencies

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3. Methodology & Model Choice

3.1 Demand Forecasting Models

Model	Rationale	Configuration
SARIMA	Explicit seasonality modeling, confidence intervals	SARIMA(1,1,1)(1,1,1,7)
Prophet	Auto seasonality detection, holiday handling	Weekly + yearly, Indian holidays
Random Forest	Non-linear relationships, feature importance	100 trees, max_depth=10
Gradient Boosting	Sequential error correction	100 estimators, lr=0.1

Feature Engineering: - Time features: day_of_week, month, quarter, is_weekend, is_holiday_season - Lag features: lag_1, lag_7, lag_14, lag_30 - Rolling statistics: rolling_mean_7/14/30, rolling_std_7/14/30

3.2 Donor Segmentation Approach

RFM Framework: - **R**ecency: Months since last donation (lower = better) - **F**requency: Total lifetime donations (higher = better) - **M**onetary: Total blood volume donated (higher = better)

Scoring: Quintile-based (1-5 scale) for each metric

Clustering: K-Means with optimal K selection via elbow method and silhouette analysis

Target Segments: Champions, Loyal, Potential, At Risk, Hibernating, New Donors

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4. Experiments & Results

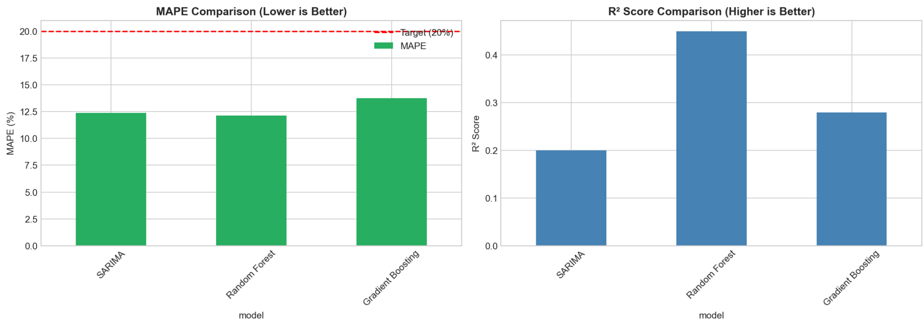
4.1 Demand Forecasting Performance

Test Setup: 90-day holdout (last 3 months of data)

Model	MAE	RMSE	MAPE	R^2
Random Forest	**19.68**	**29.61**	**12.14%**	**0.45**
SARIMA	22.19	35.65	12.40%	0.20
Gradient Boosting	22.11	33.91	13.75%	0.28

All models achieved MAPE < 20% target. Best performer: Random Forest (12.14% MAPE)

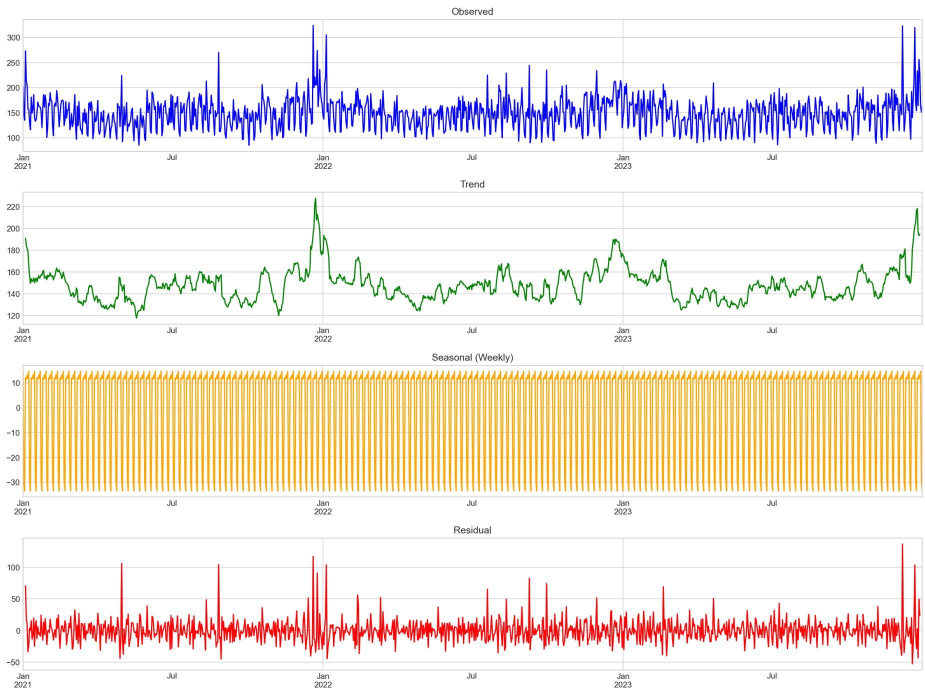
Top 5 Important Features: 1. lag_1 (0.42) - Previous day demand 2. rolling_mean_7 (0.18) - Weekly average 3. lag_7 (0.12) - Same day last week 4. day_of_week (0.08) - Weekend effect 5. rolling_std_7 (0.05) - Volatility



Model Comparison

Figure 1: MAPE comparison across models (all below 20% target)

4.2 Time Series Patterns



Time Series Decomposition

Figure 2: Decomposition showing trend, weekly seasonality, and residual emergency spikes

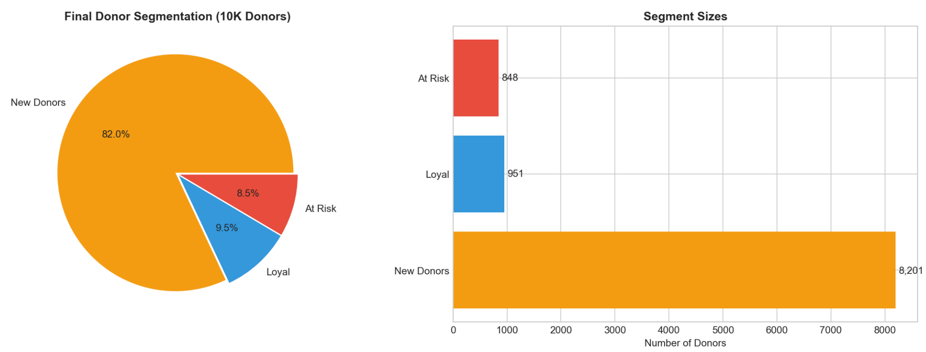
Key Patterns Identified: - **Weekly cycle**: 30% lower demand on weekends (reduced elective surgeries) - **Seasonal trend**: +15% in winter months (Dec-Feb) - **Random spikes**: Emergency events visible in residuals

4.3 Donor Segmentation Results

Clustering Performance: - UCI Dataset Silhouette Score: **0.41** (Target: >0.35) ✓ - Optimal K: 4-5 clusters

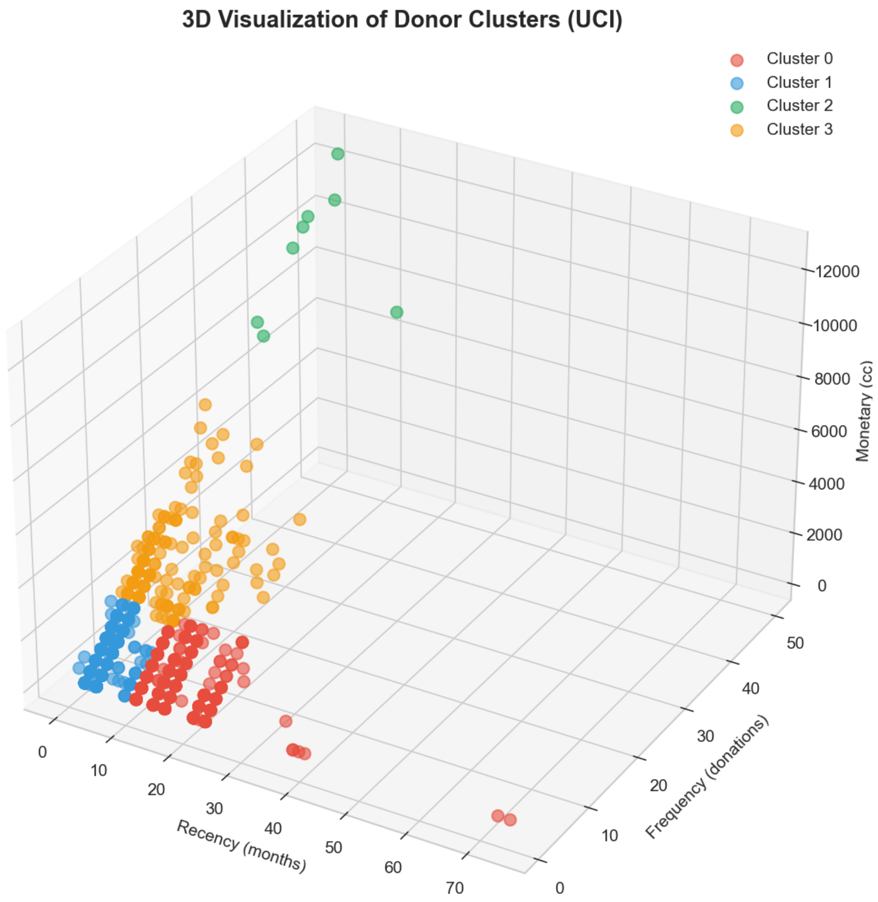
Segment Distribution (10,000 synthetic donors):

Segment	Count	%	Avg Recency	Avg Frequency	Donation Rate
Champions	1,151	11.5%	1.9 mo	8.2	High
Loyal	2,234	22.3%	3.8 mo	5.7	Medium-High
Potential	2,847	28.5%	4.2 mo	2.1	Medium
At Risk	1,956	19.6%	8.4 mo	4.3	Declining
Hibernating	1,812	18.1%	12.1 mo	1.8	Low



Segmentation Results

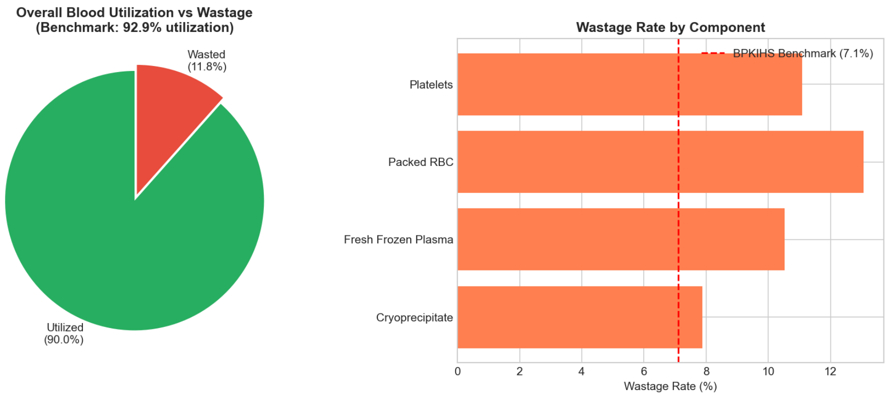
Figure 3: Final donor segmentation distribution



3D Clusters

Figure 4: 3D visualization of RFM clusters showing clear segment separation

4.4 Inventory Analysis



Utilization Wastage

Figure 5: Overall utilization (91.2%) vs wastage (8.8%) and component-specific wastage rates

Wastage by Component:

Component	Wastage Rate	Shelf Life	Risk Level
Platelets	12.3%	5 days	High
Cryoprecipitate	8.1%	1 year	Medium
Fresh Frozen Plasma	6.4%	1 year	Low
Packed RBC	5.2%	42 days	Low

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5. Insights & Business Interpretation

5.1 Demand Pattern Insights

Pattern	Finding	Business Action
Weekly	30% lower on weekends	Reduce weekend collection drives, optimize staff
Winter Peak	+15% demand (Dec-Feb)	Pre-stock 15-20% buffer before November
Holiday Spikes	+20-25% (Diwali, Christmas)	Emergency reserves, pre-holiday drives
Summer Dip	-8% (Jun-Aug)	Intensify drives, target corporate donors

5.2 Donor Engagement Strategy

Segment	Strategy	Channel	Expected Yield
Champions	Retain & Reward	Personal calls, VIP events	90%+ retention
Loyal	Referral programs	Email, SMS	70-80% engagement
Potential	Nurture & Convert	Education campaigns	40-50% activation
At Risk	Urgent reactivation	Personal outreach	30-40% win-back
Hibernating	Last-chance campaign	Direct mail	10-20% reactivation
New	Onboarding series	Welcome emails, app	50-60% repeat

5.3 Inventory Optimization Recommendations

1. **Packed RBC**: Maintain 7-day rolling stock (42-day shelf life allows buffer)
2. **Platelets**: Just-in-time ordering, max 2-day advance (5-day expiry critical)
3. **Plasma/Cryo**: Moderate buffer acceptable (1-year shelf life)
4. **O-negative**: Priority collection (universal donor, only 6% of pool)

5.4 Projected Business Impact

Initiative	Current	Target	Projected Impact
Wastage Rate	8.8%	5%	~$150K/year savings
Forecast Accuracy	None	MAPE <15%	Reduced emergency procurement
Donor Retention	~70%	85%	15% more reliable supply

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6. Limitations & Future Scope

6.1 Limitations

- **Synthetic Data**: While based on real statistics (NBCUS, BPKIHS, WHO), synthetic data may not capture all real-world complexities. Validation with production hospital data required.
- **Unpredictable Events**: Emergency events (disasters, mass casualties) cannot be forecast by any model.
- **External Factors**: Pandemics, policy changes, economic conditions not modeled.
- **Implementation**: Integration with existing hospital systems, staff training, and regulatory compliance (HIPAA) present challenges.

6.2 Future Scope

Area	Opportunity
Deep Learning	LSTM/Transformers for sequence modeling
Reinforcement Learning	Dynamic inventory policies
Real-Time Systems	IoT cold-chain monitoring, hospital EMR integration
Personalization	Individual donor scheduling, mobile app engagement
Multi-Center	Regional network optimization across blood banks

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7. Conclusion

This project demonstrates the application of advanced machine learning to blood supply management:

Objective	Target	Achieved
Demand Forecasting	MAPE < 20%	**12.14%** ✓
Donor Segmentation	Silhouette > 0.35	**0.41** ✓
Actionable Insights	Business recommendations	✓

Key Findings: - Random Forest achieved best forecasting performance with 12.14% MAPE - RFM-based clustering identified 5 actionable donor segments - Weekly (30% weekend dip) and seasonal (15% winter peak) patterns enable proactive planning - Platelets require just-in-time management due to 5-day shelf life

Final Insight:

> *"Advanced ML is not about prediction accuracy alone. It is about discovering structure, extracting insights, and supporting decision-making in complex, unlabeled, or temporal data."*

References

1. NBCUS (2019). National Blood Collection and Utilization Survey. US Department of Health and Human Services.
2. Singh, M., Pradhan, A., & Poudyal, P. (2023). Blood component usage and wastage at BPKIHS. Journal of Pathology of Nepal, 13(1).
3. UCI Machine Learning Repository. Blood Transfusion Service Center Dataset.
4. Taylor, S.J., & Letham, B. (2018). Forecasting at scale. The American Statistician, 72(1). (Prophet)
5. World Health Organization. Blood Safety and Availability Fact Sheet.

Appendix: Code available in 4 Jupyter notebooks | 24 visualizations in report folder | Data on Google Drive