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# HemoLink AI: An Intelligent Machine Learning Framework for Emergency Blood Donor Response Prediction and Healthcare Coordination

Vishal Singh
Department of Computer Science and Engineering
United College of Engineering & Research
Prayagraj, India

***Abstract*—Coordination of emergency blood remains one of the major logistical problems facing health care organizations, since the time lag involved in locating appropriate donors may affect the patient's condition. Traditional models for coordinating blood use conventional methods of communication between the donors and a fixed route to process requests from hospitals.**

**This paper presents HemoLink AI, an intelligent machine learning-driven emergency healthcare coordination framework designed to improve donor-response prediction and emergency blood donor prioritization. The proposed framework integrates synthetic healthcare dataset generation, donor-response behavioural modelling, predictive machine learning classification, explainable artificial intelligence analysis, and healthcare-oriented operational analytics within a unified coordination architecture.**

**A synthetic healthcare dataset containing 5000 donor-request interaction records was generated using probabilistic behavioural simulation techniques to emulate realistic emergency donor-response patterns. Comparative evaluation was conducted using Logistic Regression and Random Forest classifiers for donor-response prediction.**

**Experimental results demonstrated strong classification capability, with both models achieving ROC-AUC scores above 0.82. Logistic Regression achieved superior recall-oriented performance and interpretability, while Random Forest demonstrated improved precision and feature importance analysis capability. Explainable AI evaluation further identified donor proximity, donor activity behaviour, cooldown eligibility, and reliability score as major predictive factors influencing donor responsiveness.**

**The proposed HemoLink AI framework contributes toward intelligent, transparent, and scalable emergency healthcare coordination systems capable of improving donor prioritization efficiency and healthcare operational decision-support during critical medical situations.**

***Index Terms*—Healthcare AI, Emergency Blood Coordination, Machine Learning, Donor Response Prediction, Explainable Artificial Intelligence, Healthcare Informatics, Logistic Regression, Random Forest**

## I. INTRODUCTION

Ensuring timely access to blood during medical emergencies remains a persistent challenge for healthcare organizations. In situations involving trauma care, major surgeries, accidents, or other critical conditions, delays in locating suitable and willing blood donors can directly affect treatment outcomes. Although many blood donation platforms maintain donor records and communication channels, the process of identifying donors who are both eligible and likely to respond often remains inefficient.

The growing adoption of healthcare informatics and artificial intelligence has created opportunities to improve emergency coordination through data-driven decision-making and predictive analytics [1], [2]. Machine learning techniques have been successfully applied in several healthcare domains, including clinical decision support, resource allocation, and emergency management, demonstrating their potential to enhance operational efficiency.

Most existing blood donation systems concentrate on donor registration, request broadcasting, and inventory-related functions. While these capabilities are important, they generally do not provide mechanisms for predicting donor responsiveness or prioritizing potential donors based on behavioural and operational factors. As a result, emergency coordinators may still spend valuable time contacting donors who are unlikely to respond.

To address this gap, HemoLink AI is introduced as a machine learning-driven framework for emergency blood donor coordination. Rather than treating all eligible donors equally, the framework estimates the likelihood of donor participation using historical and behavioural indicators. The proposed approach combines synthetic healthcare data generation, predictive classification models, explainable AI analysis, and operational evaluation within a unified coordination workflow.

For prediction, multiple donor-related attributes are considered, including donor distance, reliability score, activity history, urgency level, cooldown eligibility, and donation records. Logistic Regression and Random Forest classifiers were selected for comparative analysis because they provide a balance between predictive capability and interpretability. The evaluation focuses not only on classification performance but also on the practical suitability of the models for emergency healthcare coordination.

Experimental findings indicate that both models are capable of identifying donor-response patterns with good predictive performance while maintaining transparency in the decision-making process. In addition, explainability analysis highlights the factors that contribute most strongly to donor responsiveness, supporting more informed coordination decisions during emergency situations.

The main contributions of this work are summarized as follows:

- Development of a machine learning-driven framework for emergency blood donor coordination and donor-response prediction.
- Creation of a synthetic healthcare dataset generation methodology to simulate donor-response behaviour in emergency scenarios.
- Comparative assessment of Logistic Regression and Random Forest models for donor-response classification.
- Integration of explainable AI techniques to improve transparency and interpretability of prediction outcomes.
- Development of visualization and evaluation components for analyzing healthcare coordination performance.

## II. RELATED WORK

Research in healthcare informatics has increasingly focused on improving emergency response systems through intelligent decision-support technologies and data-driven operational frameworks [1], [3]. These developments have encouraged the adoption of predictive analytics and machine learning techniques in several healthcare coordination applications.

A considerable amount of prior work has been dedicated to blood donation management platforms. Most of these systems provide functionalities such as donor registration, blood inventory monitoring, and emergency request dissemination [4], [5]. While such platforms improve communication between donors and healthcare organizations, donor selection is often performed using predefined rules or manual coordination procedures. This can create delays when rapid responses are required during emergency situations.

Machine learning has emerged as a practical approach for addressing prediction and prioritization problems in healthcare environments. Previous studies have reported successful applications of algorithms including Logistic Regression, Decision Trees, Random Forests, and ensemble-based methods for healthcare forecasting, risk assessment, and operational planning [2], [6]. These approaches demonstrate the potential of predictive models to support faster and more informed decision-making processes.

Several researchers have also examined factors that influence emergency healthcare coordination effectiveness. Variables such as donor availability, geographical proximity, response behaviour, and logistics constraints have been identified as important considerations for improving emergency response outcomes [7], [8]. Despite these contributions, relatively few studies focus specifically on predicting donor responsiveness before notifications are issued.

Another important area of investigation is explainable artificial intelligence. As machine learning models become increasingly involved in healthcare decision support, transparency and interpretability have gained significant attention [9]. Healthcare practitioners often require an understanding of the reasoning behind model predictions before incorporating them into operational workflows. Consequently, explainable AI techniques are becoming an essential component of trustworthy healthcare analytics systems.

Building upon these research directions, HemoLink AI combines donor-response prediction, emergency donor prioritization, comparative machine learning evaluation, and explainable AI analysis within a single healthcare coordination framework. The objective is not only to estimate donor responsiveness but also to provide interpretable insights that can assist emergency coordination decisions.

## III. SYSTEM ARCHITECTURE

The HemoLink AI platform is designed as an intelligent emergency healthcare coordination framework that integrates machine learning-driven donor-response prediction, geospatial emergency coordination, donor management, and healthcare logistics optimization.

The system architecture follows a modular full-stack design consisting of frontend interaction modules, backend coordination services, machine learning prediction components, database management systems, and emergency communication workflows.

### *A. Frontend Layer*

The frontend module is responsible for handling the users' interaction and accessibility in the emergency coordination process. The frontend module makes it possible to interact with the system through its features like submission of an emergency request for blood donation, donor registration, request tracking, and notification handling.

The frontend architecture is designed to support responsive emergency coordination workflows with minimal interaction latency and simplified emergency request accessibility.

### *B. Backend Coordination Layer*

The backend layer manages emergency request processing, donor coordination workflows, authentication services, request prioritization, and machine learning inference integration.

The backend coordination module performs the following primary operations:

- Emergency blood request processing
- Donor eligibility verification
- Intelligent donor prioritization
- Request routing and coordination
- Notification management
- Donor-response tracking

The backend additionally handles secure communication between the machine learning prediction engine and healthcare coordination modules.

The implementation architecture of the proposed HemoLink AI framework utilizes React.js for frontend interface development, FastAPI for backend API services, Firebase OTP authentication for secure user verification, and MySQL for donor-record and healthcare coordination data management. The machine learning pipeline was implemented using Python-based libraries including Scikit-learn, Pandas, NumPy, and Matplotlib for predictive analytics, model evaluation, and explainable AI visualization.

### C. Machine Learning Integration Layer

The machine learning layer is responsible for predictive donor-response analysis and intelligent donor prioritization.

The trained classification models evaluate donor-response probability using behavioural, logistical, and healthcare-oriented features such as donor proximity, reliability score, donation eligibility, donor activity history, and urgency level.

The machine learning pipeline supports:

- Predictive donor-response ranking
- Emergency donor prioritization
- Explainable AI analysis
- Feature importance evaluation
- Comparative model evaluation

The prediction outputs are integrated into the emergency coordination workflow to improve donor selection efficiency during critical healthcare scenarios.

### D. Database and Data Management Layer

The database layer stores donor records, emergency requests, donor-response history, blood inventory information, and predictive healthcare analytics data.

The data management architecture supports scalable healthcare coordination operations and enables continuous donor-response behaviour analysis for future predictive optimization.

### E. Emergency Coordination Workflow

The emergency workflow begins when a healthcare entity or patient submits a blood request through the platform. The backend system validates the request and forwards the request attributes to the machine learning prediction module.

The prediction engine evaluates donor-response probability scores for eligible donors and prioritizes donors according to predicted responsiveness, availability, and emergency relevance. The prioritized donor list is then used for emergency notification routing and coordination.

The overall workflow improves emergency donor identification efficiency and reduces manual coordination overhead during time-critical healthcare situations.

## IV. PROPOSED METHODOLOGY

The proposed HemoLink AI framework introduces an intelligent donor-response prediction and emergency blood coordination methodology designed to improve emergency healthcare logistics and donor prioritization efficiency. The methodology integrates synthetic healthcare data generation, machine learning-based donor-response prediction, feature engineering, comparative classification analysis, and explainable artificial intelligence techniques.

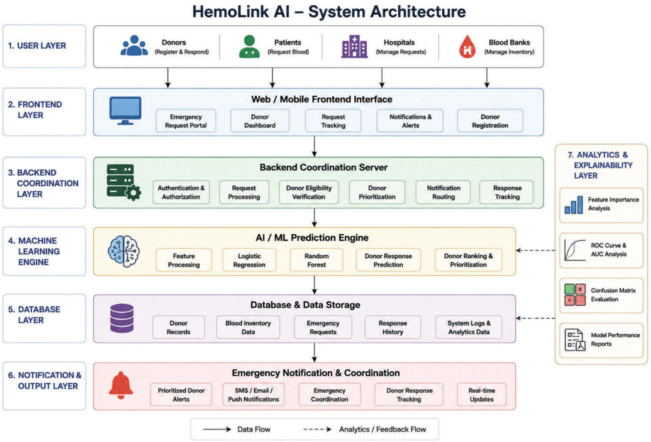

Fig. 1. System architecture of the proposed HemoLink AI emergency healthcare coordination framework.

The overall workflow of the proposed methodology consists of five major stages: synthetic dataset generation, data preprocessing, feature engineering, machine learning model training, and performance evaluation.

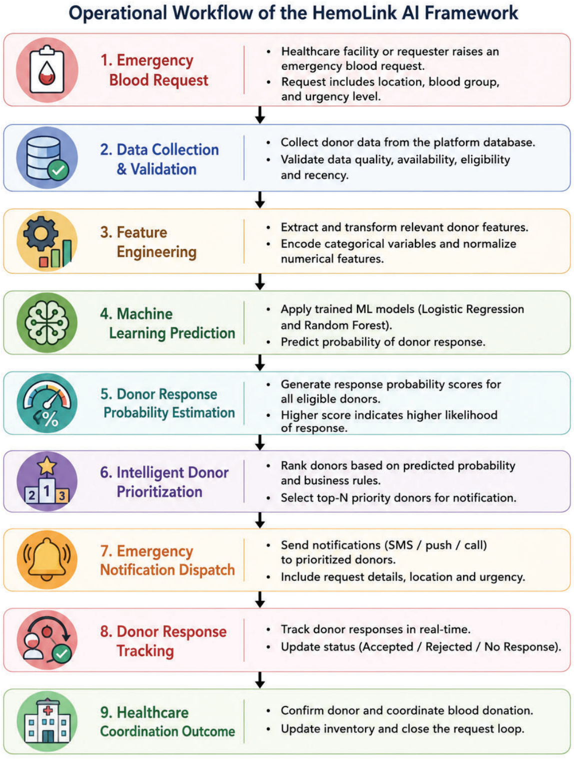

Fig. 2. Operational workflow of the HemoLink AI framework.

### A. Synthetic Dataset Generation

Due to the absence of publicly available emergency donor-response datasets, a synthetic healthcare dataset was generated to simulate realistic donor-response behaviour during emergency blood request scenarios. The generated dataset contains 5000 donor-request interaction records with probabilistic behavioural characteristics designed to emulate real-world emergency coordination patterns.

The dataset includes multiple healthcare-oriented and behavioural attributes such as donor proximity, reliability score, availability status, urgency level, donor activity history, blood group rarity, cooldown eligibility, and donor verification status.

The synthetic data generation process intentionally incorporates noisy and non-uniform behavioural distributions to improve realism and reduce overfitting risks during model training.

### B. *Feature Engineering*

Feature engineering was performed to transform raw donor-response attributes into machine learning-compatible predictive variables. Several operational and behavioural healthcare indicators were incorporated to improve donor-response prediction quality.

The selected features include donor distance, reliability score, donation history, response rate, urgency level, donor activity patterns, cooldown constraints, blood group rarity, and account verification status.

Categorical variables such as urgency level and blood group were encoded using Label Encoding techniques before model training.

### C. *Machine Learning Pipeline*

The proposed framework formulates donor-response prediction as a binary classification problem where the model predicts whether a donor is likely to respond successfully to an emergency blood request.

Two machine learning classifiers were evaluated:

- Logistic Regression
- Random Forest Classifier

Logistic Regression was selected as an interpretable baseline healthcare model due to its transparency and suitability for explainable medical decision-support systems. Random Forest was selected to evaluate nonlinear predictive learning capability and feature interaction modelling.

The dataset was divided into training and testing subsets using an 80:20 split ratio to ensure unbiased performance evaluation.

### D. *Model Evaluation Strategy*

The trained models were evaluated using multiple classification metrics including accuracy, precision, recall, F1-score, confusion matrix analysis, feature importance analysis, and Receiver Operating Characteristic (ROC) curve evaluation.

Special emphasis was placed on recall performance because emergency healthcare coordination systems prioritize minimizing missed donor opportunities over reducing excess notifications.

Feature importance analysis was additionally conducted using the Random Forest classifier to improve model interpretability and explainability for healthcare-oriented deployment scenarios.

## V. MACHINE LEARNING MODELS

The proposed HemoLink AI framework formulates emergency donor-response prediction as a supervised binary classification problem. The objective of the predictive system is to estimate the probability that a donor will successfully respond to an emergency blood request based on behavioural, operational, and healthcare-oriented features.

### A. *Problem Formulation*

Given a donor feature vector:

$$X = x_1, x_2, x_3, ..., x_n \tag{1}$$

the predictive model estimates the probability:

$$P(Y = 1 \mid X) \tag{2}$$

where:

- (Y = 1) represents successful donor response
- (Y = 0) represents non-response

The feature vector incorporates multiple predictive attributes including donor proximity, reliability score, donation eligibility, urgency level, donor activity patterns, response history, and healthcare coordination factors.

### B. *Logistic Regression Model*

Logistic Regression was selected as the baseline interpretable healthcare-oriented classification model due to its transparency and suitability for explainable healthcare decision-support systems.

The Logistic Regression classifier estimates donor-response probability using the sigmoid activation function:

$$P(Y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \tag{3}$$

where:

- $x_i$ represents predictive donor-response features
- $\beta_i$ represents learned model coefficients

The model predicts donor responsiveness by estimating the probability of successful emergency donor participation based on learned behavioural relationships.

### C. *Random Forest Classifier*

The Random Forest classifier was incorporated to evaluate nonlinear predictive learning capability and feature interaction modelling.

Random Forest is an ensemble learning approach that combines multiple decision trees to improve classification robustness and reduce overfitting risk. Each decision tree independently evaluates donor-response behaviour using randomized feature subsets and training samples.

The final prediction is generated using majority voting across multiple decision trees:

$$\hat{Y} = \text{mode}(T_1(X), T_2(X), \ldots, T_k(X)) \tag{4}$$

where:

- $T_i(X)$ represents the prediction of the $i^{th}$ decision tree
- $k$ represents the total number of trees

The Random Forest classifier additionally supports feature importance analysis, which improves explainability and healthcare-oriented interpretability.

### D. *Classification Evaluation Metrics*

The proposed models were evaluated using multiple classification metrics including accuracy, precision, recall, and F1 score.

Accuracy measures the overall prediction correctness:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

Precision evaluates the proportion of correctly predicted positive donor responses:

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

Recall measures the ability of the model to identify responsive donors:

$$Recall = \frac{TP}{TP + FN} \tag{7}$$

F1-score provides the harmonic mean of precision and recall:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{8}$$

Special emphasis was placed on recall-oriented evaluation because minimizing missed donor opportunities is operationally critical in emergency healthcare coordination systems.

## VI. EXPERIMENTAL SETUP

The experimental evaluation of the proposed HemoLink AI framework was conducted using a synthetic donor-response healthcare dataset generated through probabilistic behavioural simulation techniques.

### A. *Dataset Configuration*

The experimental dataset contains 5000 donor-request interaction records. Each record represents a potential interaction between an emergency blood request and a registered donor. The objective was to model situations that commonly occur during emergency blood coordination, where donor behaviour, eligibility, and availability influence response outcomes.

Several donor-related and healthcare-oriented attributes were included during dataset generation. These features capture factors such as geographical distance, donor reliability, recent activity, donation eligibility, blood group rarity, emergency urgency, historical responsiveness, and verification status. Rather than assigning completely random values, probabilistic distributions were used so that the generated data better reflects realistic donor-response behaviour and uncertainty.

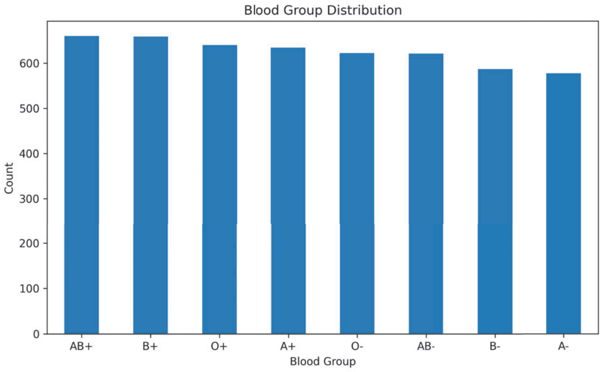

Fig. 3. Distribution of blood group categories in the synthetic healthcare dataset.

TABLE I
DATASET FEATURE DESCRIPTION USED IN HEMOLINK AI

| **Feature** | **Description** |
|---|---|
| distance_km | Distance between donor and emergency request location |
| reliability_score | Historical donor reliability index |
| availability_status | Current donor availability status |
| urgency_level | Emergency request priority level |
| donations_count | Total historical blood donations |
| response_rate | Historical donor response rate |
| account_age_months | Donor account age in months |
| blood_group | Donor blood group category |
| blood_group_rarity | Blood group rarity indicator |
| request_hour | Emergency request generation hour |
| donor_last_active_days | Recent donor platform activity measure |
| cooldown_remaining | Remaining donation cooldown duration |
| verified_status | Donor account verification status |
| responded | Target donor-response classification label |

### B. *Dataset Attribute Description*

The synthetic healthcare dataset used in this study consists of behavioural, operational, and healthcare-related variables that may influence donor responsiveness. Table I summarizes the attributes selected for predictive modelling.

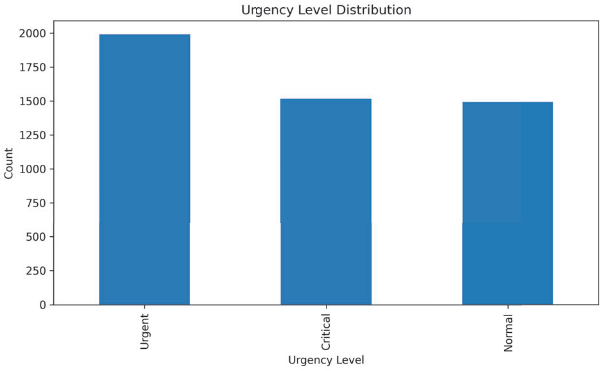

Fig. 4. Distribution of emergency urgency levels in the generated dataset.

### C. *Training and Testing Strategy*

For model development and evaluation, the dataset was divided into training and testing subsets using an 80:20 split. A fixed random state was maintained throughout experimentation

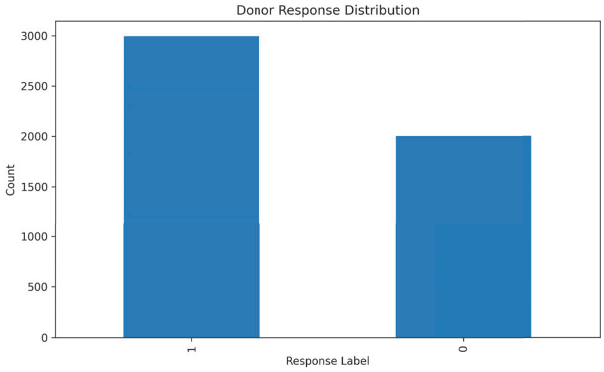

Fig. 5. Distribution of donor-response classification labels in the synthetic dataset.

to ensure reproducibility and consistent comparison between classification models.

Implementation and analysis were carried out using commonly adopted Python data science libraries, including Pandas, NumPy, Scikit-learn, Matplotlib, and Seaborn.

### *D. Evaluated Machine Learning Models*

Two supervised classification algorithms were selected for comparative evaluation:

- Logistic Regression
- Random Forest Classifier

Logistic Regression was chosen because of its interpretability and suitability for decision-support applications. Random Forest was included to examine whether ensemble learning could capture more complex relationships among donor-response variables.

### *E. Evaluation Metrics*

Performance assessment was conducted using multiple classification metrics:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix Analysis
- Receiver Operating Characteristic (ROC) Curve
- Area Under Curve (AUC)
- Feature Importance Analysis

Among these metrics, recall received particular attention because emergency blood coordination systems benefit from identifying as many potentially responsive donors as possible. Missing an available donor during a critical situation may have greater operational consequences than issuing additional notifications.

### *F. Visualization and Explainability*

Model behaviour was further examined through visualization and explainability techniques. Comparative performance plots, confusion matrices, feature-importance rankings, and ROC analysis were incorporated to support transparent evaluation of classification outcomes.

TABLE II
COMPARATIVE PERFORMANCE EVALUATION OF MACHINE LEARNING MODELS USED IN HEMOLINK AI

| Model | Accuracy | Precision | Recall | F1 Score | AUC |
|---|---|---|---|---|---|
| Logistic Regression | 77.4% | 77.9% | 89.1% | 83.1% | 0.8258 |
| Random Forest | 77.4% | 79.3% | 86.2% | 82.6% | 0.8251 |

Interpretability is especially important in healthcare-related applications, where understanding the factors behind a prediction can improve confidence in model-assisted decision making. The explainability analysis therefore provides additional insight into the donor characteristics that contribute most strongly to predicted responsiveness.

## VII. RESULTS AND EVALUATION

Performance evaluation was carried out using both Logistic Regression and Random Forest classifiers on the generated donor-response dataset. The objective was to compare predictive effectiveness, model interpretability, and practical suitability for emergency blood coordination scenarios.

For Logistic Regression, the obtained accuracy was 77.4%, with precision, recall, and F1-score values of 77.9%, 89.1%, and 83.1%, respectively. A particularly notable observation was the high recall value, indicating that the model was successful in identifying a large proportion of donors who were likely to respond. In emergency healthcare settings, this characteristic can be valuable because missed donor opportunities may delay critical medical interventions.

The Random Forest model produced the same overall accuracy of 77.4%, while achieving a precision of 79.3%, recall of 86.2%, and F1-score of 82.6%. Although its recall was slightly lower, the increase in precision suggests that the model generated fewer unnecessary donor notifications. This behaviour may help reduce communication overhead in large-scale donor coordination environments.

The comparison highlights a practical tradeoff between donor coverage and notification efficiency. Logistic Regression demonstrated stronger sensitivity toward identifying potential responders, whereas Random Forest provided more selective predictions. Depending on operational priorities, either approach may be advantageous. Situations that emphasize donor outreach may benefit from higher recall, while scenarios focused on reducing unnecessary alerts may favour improved precision.

As illustrated in Fig. 6, both classifiers demonstrated consistent predictive behaviour across the evaluation dataset. The confusion matrix analysis provides a detailed view of correctly and incorrectly classified donor-response outcomes, offering additional insight beyond aggregate performance metrics.

As shown in Fig. 7, feature importance analysis was performed using the Random Forest model to better understand the factors influencing prediction outcomes. Distance-related proximity emerged as the strongest contributor, followed by

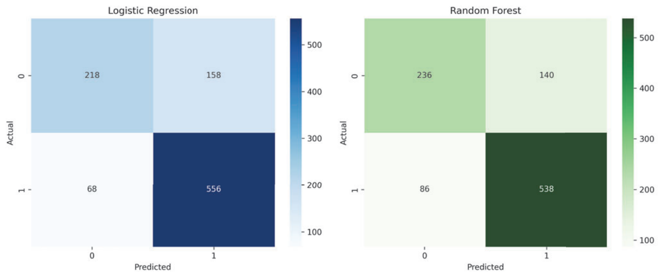

Fig. 6. Confusion matrix comparison between Logistic Regression and Random Forest models.

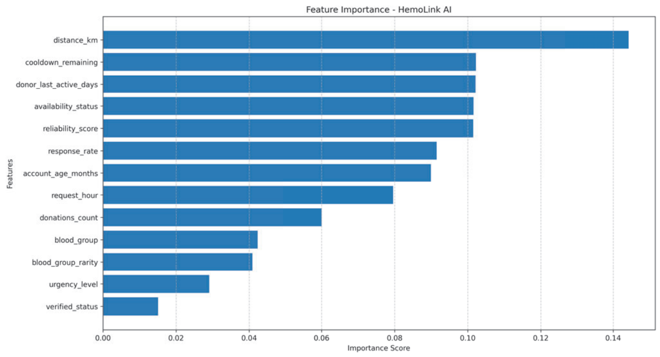

Fig. 7. Feature importance analysis of the Random Forest donor-response prediction model.

cooldown eligibility, donor activity history, availability status, and reliability score.

These results suggest that donor behaviour and operational accessibility play a larger role in response prediction than static profile information alone. Such observations are consistent with real-world emergency coordination processes, where recent activity and practical availability often influence participation more directly than demographic attributes.

The feature analysis also improves interpretability by providing visibility into how different variables contribute to prediction outcomes. This level of transparency can be beneficial when machine learning systems are used to support healthcare-related decision making.

Further evaluation was conducted using Receiver Operating Characteristic (ROC) analysis. The Logistic Regression model achieved an AUC value of 0.8258, while Random Forest obtained an AUC of 0.8251.

The ROC curves indicate that both approaches maintained strong discrimination capability on the generated dataset. The difference between the two models was relatively small, suggesting that each was effective at distinguishing responsive donors from non-responsive donors.

When considered together with the classification metrics, the results indicate that Logistic Regression offers a favourable balance between predictive performance and interpretability. Random Forest, on the other hand, provides stronger precision characteristics and valuable explainability through feature ranking. Consequently, the choice between the two models may depend on the operational requirements of the healthcare coordination environment in which the system is deployed.

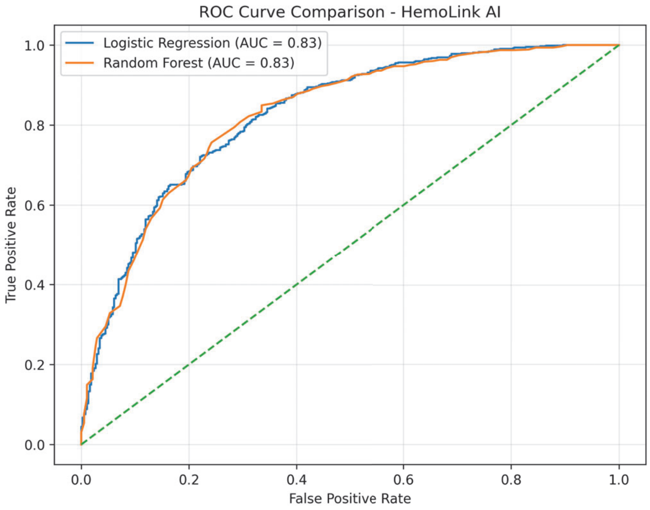

Fig. 8. ROC curve comparison between Logistic Regression and Random Forest donor-response prediction models.

## VIII. LIMITATIONS

The results obtained in this study should be interpreted in the context of several limitations.

A major limitation is the use of a synthetically generated donor-response dataset. Publicly available datasets containing detailed emergency blood donor behaviour are limited, which motivated the use of probabilistic simulation techniques for data generation. Although the dataset was designed to incorporate realistic variability in donor characteristics and response patterns, it cannot fully represent the complexities of real healthcare operations and human decision-making behaviour.

Another limitation relates to the scope of the current implementation. The work focuses primarily on donor-response prediction and analytical evaluation rather than complete real-world deployment. Practical adoption would require integration with hospital information systems, blood bank databases, geolocation services, communication infrastructure, and healthcare compliance frameworks.

The framework has also not been evaluated in live operational environments. Factors such as communication delays, network reliability, user behaviour, emergency workload fluctuations, and large-scale coordination challenges were outside the scope of the present study. Consequently, real-world performance may differ from the results observed during experimental evaluation.

From a machine learning perspective, only Logistic Regression and Random Forest classifiers were investigated. These models provided a suitable basis for comparative analysis; however, additional algorithms and optimization strategies may reveal further improvements in predictive performance. Exploring a broader range of approaches could provide a more comprehensive understanding of donor-response prediction behaviour.

Finally, the deployment of AI-assisted healthcare systems introduces important ethical and governance considerations. Issues related to donor privacy, responsible use of healthcare data, transparency of predictive decisions, and algorithmic fairness require careful attention before practical implementation in healthcare environments.

## IX. FUTURE WORK

Several opportunities exist for extending and improving the HemoLink AI framework beyond the scope of the current study.

One of the most important next steps is the incorporation of real-world hospital and blood bank datasets. Access to operational healthcare data would allow more realistic validation of donor-response prediction models and provide stronger evidence regarding system performance under practical emergency conditions.

The predictive component of the framework can also be expanded through the investigation of more advanced learning approaches. Techniques such as recurrent neural networks, graph neural networks, and transformer-based architectures may capture complex behavioural relationships that are difficult to model using traditional machine learning methods alone.

Geospatial intelligence represents another promising area for future development. By incorporating route optimization, travel-time estimation, and location-aware prioritization, donor recommendations could be adapted according to traffic conditions, geographic accessibility, and emergency logistics requirements.

The current architecture has been designed with future application-layer expansion in mind. A dedicated mobile platform combined with real-time notification services could improve donor engagement and provide faster communication during emergency situations.

Further work may also focus on strengthening explainability. Methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) could provide more detailed explanations of prediction outcomes, while fairness-aware evaluation techniques may support responsible deployment in healthcare environments.

From a data-management perspective, blockchain-assisted verification mechanisms and privacy-preserving federated learning approaches offer potential solutions for secure coordination across multiple healthcare organizations without requiring centralized sharing of sensitive donor information.

In the longer term, the framework could evolve into a broader multi-hospital coordination ecosystem capable of supporting regional blood logistics management, intelligent donor prioritization, and AI-assisted healthcare resource allocation across interconnected healthcare networks.

## X. CONCLUSION

This paper presented HemoLink AI, an intelligent emergency healthcare coordination framework designed to improve donor-response prediction and emergency blood coordination efficiency using machine learning-driven healthcare analytics.

The proposed framework integrates synthetic healthcare dataset generation, predictive donor-response classification, comparative machine learning evaluation, explainable artificial intelligence analysis, and healthcare-oriented operational intelligence within a unified emergency coordination architecture.

Comparative experimental evaluation was conducted using Logistic Regression and Random Forest classifiers. The experimental results demonstrated strong donor-response prediction capability, with both models achieving competitive classification performance and ROC-AUC scores above 0.82. On the other hand, Logistic Regression had better results in terms of the recall-oriented approach and increased explainability, while Random Forest was more successful in improving precision and in feature-importance prediction. As far as the explanation of the model is concerned, it is also worth pointing out that according to the results, such predictors as donor closeness, behaviour, cooldown eligibility, and reliability were among the most important ones. The HemoLink AI framework presented here may be considered an effort towards creating intelligent and explainable solutions for emergency coordination in the healthcare sector. While the present study utilized artificial data in the field of healthcare, the described methodology may serve as the basis for future work in the area.

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