JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

LIFE DROP: AI-BASED BLOOD DONOR FINDER AND EMERGENCY ASSISTANCE SYSTEM

[1]Dr. Girish T R, [2]Harisha H C, [3]Likitha P, [4]Manushree M, [5]Puneeth H P

[1]Professor, [2]Student, [3]Student, [4]Student, [5]Student
[1-5]Department of Artificial Intelligence and Machine Learning,
[1-5]K. S. Institute of Technology, Bengaluru, India
[1]girishshastrytr@ksit.edu.in, [2]hg818433@gmail.com, [3]likithap_aiml@ksit.edu.in, [4]manushreem_aiml@ksit.edu.in, [5]puneeth.hp26@gmail.com

Abstract : Voluntary blood donation depends on timely coordination between hospitals, blood banks and donors, yet emergency requests are often circulated manually and donor records, eligibility information and request status may be maintained separately. This paper presents Life Drop, an AI-based blood donor finder and emergency assistance system. The proposed system combines a mobile application, a deterministic ABO/Rh compatibility and eligibility pre-screening engine, a machine-learning model for donor response prediction and ranking, a demand-forecasting module, a conversational assistant for donor queries, and a notification and request-tracking workflow with donation history. A requester submits a blood request; the system identifies compatible and eligible donors, ranks them using availability, proximity and history, and notifies them, while final medical screening and verification remain with qualified staff. Implementation and validation are pending; therefore, no prediction accuracy, response-time reduction or donation-fulfilment improvement is claimed.

IndexTerms - Blood donor management, artificial intelligence, machine learning, donor matching, demand forecasting, mobile application, emergency response, healthcare.

I. INTRODUCTION

Blood is required for surgery, trauma care, childbirth complications, cancer treatment and chronic conditions such as thalassemia. Voluntary donation depends on timely communication between hospitals, blood banks and donors. In many settings, emergency requests are still circulated through phone calls and messaging groups, donor records are maintained separately, and it can be difficult to know which registered donors are compatible, eligible, nearby and willing to respond. Delays at this stage may affect the time taken to arrange a unit of blood.

Recent developments in machine learning, geolocation services and mobile computing provide methods for matching requests with suitable donors, estimating the likelihood that a donor will respond, and anticipating demand. However, donor registration, eligibility checks, request handling and inventory information are often treated as separate components.

Life Drop is designed as an integrated workflow rather than a stand-alone matching routine. It combines a mobile application for donors and requesters, a rule-based compatibility and eligibility engine, machine-learning models for donor ranking and demand forecasting, a conversational assistant, and a notification module. The system is intended as a decision-support and technology-demonstration prototype. It does not replace medical screening, laboratory blood-group verification or the decisions of a qualified blood-bank officer.

The main contributions are: (1) a mobile interface for donor registration and emergency blood requests; (2) a compatibility and eligibility pre-screening component; (3) AI-assisted ranking of donors using availability, distance and donation history; (4) demand forecasting for blood-group requirements; (5) a conversational assistant for donor queries; and (6) a donation history and audit record associated with each donor and request.

II. BACKGROUND AND RELATED WORK

A. Blood Donor Management

Blood donation systems generally involve donor recruitment, screening, collection, testing, storage and distribution. Compatibility depends on the ABO and Rh blood-group system, and donors must satisfy eligibility criteria such as age, weight, haemoglobin level, health status and the minimum interval since the last donation. Applicable national guidelines define these criteria, and the final eligibility decision rests with trained medical staff.

B. Machine Learning in Healthcare Logistics

Supervised classification can estimate whether a donor is likely to respond to a request using features such as past response behaviour, recency of donation and distance. Time-series forecasting has been studied for estimating blood-product demand and

reducing shortage or wastage. Model performance depends on data quality, class imbalance, seasonality and differences between historical and future conditions. Dataset provenance and testing conditions must therefore be documented.

C. Existing Solutions and Research Gap

Existing blood-donation applications and blood-bank portals support donor registration, request posting and stock display. These solutions demonstrate individual functions, but they do not necessarily provide the specific student-project workflow proposed here: compatibility logic, eligibility pre-screening, learned donor ranking, demand forecasting, an assistant and audit records in one application. The novelty lies in the integration and context-specific prototype, not in claiming that the individual technologies are new.

III. PROBLEM STATEMENT AND OBJECTIVES

Problem statement: Arranging blood during an emergency is challenging because it depends on manual communication, which is time-consuming and may delay the identification of suitable donors. Requests may be broadcast to all donors regardless of blood group, location or eligibility, leading to unnecessary notifications and reduced donor engagement. Donor records, request status and stock information may also be maintained separately. Therefore, an integrated AI-assisted system is proposed to register donors, match requests with compatible and eligible donors, rank them using AI, forecast demand and maintain a transparent record of each request.

The project objectives are to develop a cross-platform mobile application using React Native, Expo and TypeScript; implement a compatibility and eligibility pre-screening engine; develop a machine-learning model for donor response prediction and ranking; develop a demand-forecasting module; provide an assistant for donor queries; maintain donation history and request records; and integrate and evaluate the components.

The scope is intentionally limited to a student-scale prototype. The system provides decision support and does not replace medical examination, laboratory testing or blood-bank procedures. Location coordinates represent the device location when shared and are used only for approximate proximity ranking.

IV. SYSTEM ARCHITECTURE

The proposed architecture contains five logical layers. The mobile application layer provides the dashboard, donor profile, request creation, donor search, donation history, notifications and assistant. The rules layer applies blood-group compatibility and eligibility checks. The AI layer contains the donor-ranking model, the demand-forecasting model and the conversational assistant. The data layer manages donor profiles, requests, donation records and audit logs. The notification layer delivers alerts to selected donors.

The intended data flow is: requester submits a blood request (blood group, units, hospital, urgency) → rules engine determines compatible blood groups → eligibility filter removes donors who are not currently eligible → AI model ranks remaining donors by response likelihood and proximity → top-ranked donors are notified → donors accept or decline → requester views responses → the blood bank or hospital confirms the donation → the record is added to history.

The application, rules engine and AI models are separate modules so that the interface can be tested independently of model training. The rules engine can be verified against a compatibility table before any learned component is introduced, which helps isolate faults during development.

V. DATA PREPARATION AND MODEL DEVELOPMENT

Donor-ranking and forecasting models require data. Because real donor records are sensitive, the prototype will use synthetic or fully anonymised data unless institutional approval and consent are obtained. The data source, generation method, feature definitions, record count and permitted use should be recorded. Synthetic data should be described as such, and results obtained on it must not be presented as real-world performance.

Candidate features for donor response prediction include blood group, days since last donation, past acceptance rate, average response time, approximate distance to the hospital, time of day and urgency level. Records should be checked for missing values, inconsistent entries and duplicates. A documented split strategy should be used so that records of the same donor do not appear in both training and test partitions.

Preprocessing may include encoding of categorical variables, scaling of numeric features and handling of class imbalance. The same pipeline must be applied during training and inference. The exact algorithms and hyperparameters will be selected and documented during implementation. A model score should not be described as a calibrated probability unless calibration is evaluated.

VI. AI FEATURES

The AI-assisted functions planned for the prototype are summarised in Table I. Each function is designed to support, not replace, human decisions.

Table I. Planned AI features

AI feature	Candidate technique	Output
Compatibility matching	ABO/Rh rule engine	Compatible donor groups
Eligibility pre-screening	Rule-based checks + ML	Eligible / defer / refer
Donor response prediction	Gradient-boosted classifier	Response likelihood score
Donor ranking	Weighted scoring (distance, history)	Ranked donor list
Demand forecasting	Time-series model	Expected unit demand
Assistant chatbot	LLM with fixed guidelines	Answers to donor queries
Anomaly detection	Statistical / isolation forest	Flags for review

A. Compatibility Matching

Compatibility is determined by a deterministic ABO/Rh rule table rather than a learned model, because correctness is critical. For a requested group, the engine returns the set of acceptable donor groups. The mapping is verified against a reference table, and the blood bank performs final cross-matching.

B. Eligibility Pre-Screening

The application collects self-reported information such as age, weight, last donation date and recent illness. Rule-based checks mark a donor as possibly eligible, temporarily deferred or advised to consult staff. This is a preliminary indication only; medical screening at the donation site is authoritative.

C. Donor Response Prediction and Ranking

A classifier estimates how likely each eligible donor is to respond. The ranking combines this score with proximity and recency of donation. The ranking logic should be explainable, for example by showing which factors contributed, so that coordinators can understand and override it.

D. Demand Forecasting

A time-series model will estimate expected demand by blood group for a selected period using historical request counts. Forecasts are intended to help planning of donor camps and reminders, and are not guarantees of future demand.

E. Conversational Assistant

An assistant will answer donor queries about eligibility rules, the donation process and preparation. Its responses must be grounded in approved guideline text, and it must not provide personal medical diagnosis. For unclear or medical questions it should direct the user to qualified staff.

F. Anomaly and Duplicate Detection

Statistical methods may flag duplicate registrations, implausible donation intervals or unusual request patterns for review. Flags are prompts for human verification and do not automatically block users.

VII. MOBILE APPLICATION AND DONOR INFORMATION

The mobile application is planned as a cross-platform application using React Native, Expo and TypeScript. The dashboard summarises active requests, notifications and donation history. The Donor Profile module collects registration details and availability. The Request module allows creation and tracking of blood requests. The Search module shows ranked compatible donors to authorised coordinators. The History module presents past donations and responses. The Assistant module offers question answering.

A. Donor Workflow

A typical donor session begins with registration and profile completion. The donor enters blood group and basic details, completes the eligibility questionnaire and sets availability. When a compatible request is issued, the donor receives a notification, reviews the hospital and urgency details, and accepts or declines. After the donation is confirmed by the blood bank, the history and the next eligible date are updated.

B. Record Management

Each request record should contain a unique request identifier, requested blood group, units, hospital, urgency, status, timestamps and the list of notified donors with their responses. Each donor record should contain a donor identifier, blood group, availability, last donation date and consent status. The application should handle missing location data without preventing registration and should make clear when a distance is approximate.

VIII. EMERGENCY REQUEST AND NOTIFICATION MODULE

A requester creates a request specifying blood group, number of units, hospital and urgency. The system notifies compatible, eligible donors in ranked order, widening the radius or notifying further donors if responses are insufficient. Notification frequency should be limited to avoid fatigue. Donors may decline or pause notifications at any time.

The requester sees only the information required to coordinate, such as acceptance status and approximate availability, and donor contact details are shared only after the donor agrees. Request status (open, partially fulfilled, fulfilled, cancelled) should be updated consistently, and closed requests should stop generating notifications.

IX. EXPERIMENTAL PLAN AND EVALUATION

For donor response prediction, the model will be tested on a held-out set not used during training or model selection. The team will report the number of records, class distribution, split method and evaluation conditions. Accuracy, precision, recall and F1-score will be calculated, and a confusion matrix will be prepared. For ranking, metrics such as precision at k may be reported. For forecasting, error measures such as MAE and RMSE will be reported against a simple baseline.

Application tests will verify registration, profile entry, request creation, notification delivery, donor response handling and history retrieval. Rules-engine tests will check every blood-group combination against the compatibility table. Integration tests will verify that a request moves through the full workflow with correct status. Test cases should record objective, input, expected result, observed result and pass/fail status. No numerical performance result should be reported until measurements have been collected.

A. Evaluation Metrics

Accuracy measures the proportion of correct predictions. Precision indicates how many predicted responders actually respond, while recall measures how many actual responders are identified. The F1-score combines precision and recall. Reporting only accuracy may hide poor performance on the minority class; therefore, class-wise metrics should also be included.

B. Software Test Scenarios

Representative scenarios include a donor with no recent donation, a donor within the minimum interval, a request for a rare blood group, no compatible donors nearby, denied location permission, duplicate registration, repeated requests, unavailable network access and notification failure. The expected behaviour should be documented before testing and actual observations recorded during execution.

X. EXPECTED RESULTS AND DISCUSSION

The expected outcome is a working student prototype that demonstrates integration of donor registration, compatibility and eligibility checks, AI-assisted ranking, demand forecasting, an assistant and request tracking. Deliverables include a mobile application, a trained ranking model, a forecasting module, a request workflow and a technical evaluation report.

Reduced response time, higher fulfilment rates or improved donor retention are potential longer-term benefits and cannot be concluded from a prototype alone. Such claims require controlled pilots with a blood bank or hospital and proper measurement. The technical contribution is primarily integration and demonstration. The project does not claim that machine-learning ranking, forecasting or mobile applications are individually new.

XI. LIMITATIONS, SAFETY AND ETHICAL CONSIDERATIONS

Models trained on synthetic or small datasets may not generalise to real donor populations. Response behaviour is influenced by factors the system cannot observe. Distance estimates from device location may be approximate. Forecasts may be inaccurate during unusual events such as accidents or disease outbreaks.

Blood-group information entered by users is self-reported and must be verified by laboratory testing before use. The system must never imply that it can certify a donor as medically fit or a unit as safe. Ranking should not be used to exclude donors unfairly, and fairness across areas and groups should be examined. Predictions and rankings should be presented as suggestions requiring coordinator confirmation. Donation must remain voluntary, and the system should not pressure donors or offer payment for blood.

XII. IMPLEMENTATION WORKFLOW

The implementation is organised into sequential activities. First, the mobile application screens and navigation are developed using Expo, React Native and TypeScript. Second, the compatibility and eligibility rules are implemented and unit-tested. Third, a synthetic or anonymised dataset is prepared and the ranking and forecasting models are trained and evaluated using a documented split. Fourth, the models are connected to the application through the chosen inference interface. Fifth, the notification module, request tracking and history are integrated. Finally, end-to-end scenarios are executed and documented.

A. Software Integration

The response from the ranking service should contain donor identifiers, scores and contributing factors in a format the application can interpret. If inference fails, the application should fall back to rule-based ordering by distance and recency instead of showing incomplete results. Model and preprocessing versions should be documented together so that later updates do not create incompatibilities.

XIII. FUNCTIONAL AND NON-FUNCTIONAL REQUIREMENTS

The functional requirements include donor registration, eligibility questionnaire, blood-request creation, compatibility matching, AI-based ranking, notification delivery, donor accept/decline, request tracking, donation history, demand forecast display and an assistant. The application should also handle missing location permission and failed notifications without crashing.

Non-functional requirements include usability, maintainability, reliability, low-latency matching, privacy-aware storage, auditability and clear language that does not imply medical certainty.

XIV. RISK ANALYSIS AND MITIGATION

A major risk is incorrect compatibility or eligibility output, mitigated by deterministic rules, exhaustive testing against a reference table and mandatory staff verification. A further risk is over-reliance on model scores; the interface should describe rankings as suggestions. Notification fatigue can be reduced by limiting alerts and respecting preferences. Data misuse is a risk addressed by access control and consent. Fake or malicious requests can be reduced by requester verification and anomaly flags.

XV. DATA PRIVACY AND SECURITY

Blood group, health-related answers, contact details and location are sensitive personal data. The application should collect only what is necessary, explain its use and obtain explicit consent. Access to records should be limited by role, and communication should be encrypted if a remote backend is used. Retention and deletion options should be provided, and the design should be reviewed against applicable data-protection law, including India's Digital Personal Data Protection Act, 2023. Donor contact details should not be disclosed without the donor's agreement.

XVI. EXPECTED DELIVERABLES

The planned deliverables are: (1) a cross-platform Life Drop mobile application; (2) a compatibility and eligibility engine; (3) a donor-ranking model; (4) a demand-forecasting module; (5) an assistant for donor queries; (6) request tracking and donation history; (7) privacy and consent handling; and (8) project documentation containing implementation details and test observations.

XVII. FUTURE WORK

Future development may include integration with licensed blood-bank management systems, real-time inventory updates, multilingual assistant support including regional languages, offline operation, and improved route and travel-time estimation. Pilot studies with hospitals and blood banks could assess usability and measure response time. Any real-world deployment would require institutional approval, regulatory compliance, security assessment and clinical oversight.

XVIII. CONCLUSION

This paper presents Life Drop, an AI-based blood donor finder and emergency assistance system proposed as a student prototype. The system integrates a mobile application, rule-based compatibility and eligibility checks, machine-learning donor ranking, demand forecasting, a conversational assistant and request tracking. The evaluation plan includes classification and forecasting metrics, rules-engine verification, application tests and end-to-end integration testing. The prototype is intended to demonstrate a possible workflow; its real-world effectiveness and benefits must be established through measured results and pilot validation.

ACKNOWLEDGMENT

The authors acknowledge the Department of Artificial Intelligence and Machine Learning, K. S. Institute of Technology, Bengaluru, for academic support and access to institutional learning resources. The authors also acknowledge the project guide and faculty members for guidance and feedback during the development of this project.

REFERENCES

[1] Cite published studies on machine-learning-based blood donor response prediction and blood demand forecasting after verifying authors, title, venue, year and DOI from the publisher record.

[2] Cite the national blood-transfusion and donor-eligibility guidelines used for the rule set (issuing authority, document title, version and access date).

[3] Cite the dataset or synthetic-data generation method used for training and evaluation, with its source, version and access date.

[4] Digital Personal Data Protection Act, 2023, Government of India. Verify official citation details.

[5] Cite the weather/maps/notification service providers and the React Native, Expo and chosen machine-learning library documentation wherever their APIs are used.