STUDY OF ALGORITHMS FOR BLOOD BANK MANAGEMENT SYSTEM

Prof. Yogita More[1], Ayush Jangir[2], Abhishek Shitole[3], Ashish Gangarde[4], Ameya Tapkire[5], Arihant Pawar[6]
[1](Professor, SRCOE, Department of Computer Engineering, Pune)
[2],[3],[4], [5],[6](Student, SRCOE, Department of Computer Engineering, Pune)

Abstract: *The blood compatibility matching, request prioritization, and donor eligibility algorithms are designed to enhance the safety and efficiency of blood bank management systems. Each algorithm serves a specific function, ensuring that blood transfusions, resource allocation, and donor evaluations are conducted securely and effectively. The Blood Compatibility Matching Algorithm uses a decision tree approach, assessing ABO and Rh blood types to determine compatibility. It ensures safe transfusions by checking compatibility rules, returning a positive match for compatible blood types or a denial if they are incompatible. This algorithm, while efficient and reliable, may not account for rarer antigen profiles in unique cases. Lastly, the Donor Eligibility Algorithm assesses potential donors' suitability based on health data and donation history. This rule based and Support Vector Machine (SVM) approach first screens donors through basic criteria (e.g., age, weight) and then uses SVM for complex health metrics, ensuring safety and quality in the blood supply. If a donor passes both stages, they are marked eligible; otherwise, they are deemed ineligible. This approach is comprehensive, though it may need frequent updates as health standards evolve and could be sensitive to inconsistent health data. These algorithms together improve blood bank management by ensuring compatibility, prioritizing urgent cases, and maintaining high donor standards, contributing to safer and more efficient blood management.*

Keywords: *Donor management, Inventory tracking, Blood donation, Donor Eligibility, Blood Compatibility Match*

I. INTRODUCTION

The blood bank management system relies on a set of carefully designed algorithms to ensure safe, efficient, and reliable handling of blood transfusion needs. The algorithms (Blood Compatibility Matching, Request Prioritization, and Donor Eligibility) are essential in meeting clinical standards, managing scarce resources, and safeguarding both patients and donors. Blood Compatibility Matching Algorithm is designed to ensure the compatibility of blood types between donors and recipients, using the ABO and Rh blood group systems as the foundation. Through a decision tree approach, it assesses compatibility by systematically checking for ABO type compatibility (e.g., type O being a universal donor) and Rh factor compatibility (e.g., Rh negative recipients requiring Rh negative blood). The result is a binary output that either approves or denies the transfusion based on compatibility, preventing adverse reactions.

Donor Eligibility Algorithm ensuring the safety and suitability of donors is crucial for maintaining blood quality. This algorithm assesses potential donors based on health standards and donation history. It uses a rule-based system to enforce straightforward eligibility criteria (e.g., age, weight, and donation frequency) and an SVM model to evaluate complex health factors like hemoglobin levels and blood pressure. This dual approach filters eligible donors who meet both basic and advanced health requirements. Together, these algorithms create a robust framework that supports safe transfusions, prioritizes urgent cases, and maintains high standards for blood donations, enhancing the overall effectiveness of blood bank operations.

II. LITERATURE REVIEW

Diogo F. Pacheco et al. in the paper, Characterizing Organ Donation Awareness from social media, (2017), examines how social media, specifically Twitter, can act as a "social sensor" to gauge public awareness of organ donation across different U.S. regions. The authors hypothesize that analyzing organ-related conversations on Twitter can provide insights into public engagement with organ donation and even highlight geographical variations in awareness related to specific organs. The study's approach involves collecting and analyzing tweets over one year using specific keywords related to organ donation. By segmenting tweets based on mentions of organs (e.g., heart, kidney), the authors aim to characterize public interest in these organs within the context of organ donation. This methodology allows for the exploration of public discourse on Twitter as an indicator of awareness and potential disparities across regions in the United States. The paper's results indicate that Twitter conversations about organ donation correlate with actual organ transplantation rates, suggesting that social media could serve as a valuable tool for monitoring public sentiment and awareness. Notably, the study finds that the popularity of specific organs in Twitter discussions varies by region, which could reflect regional health disparities or cultural differences. For example, Kansas exhibited an unusually high volume of discussions around kidney donation, consistent with the state's known surplus of deceased kidney donors. The study concludes that social media data offers a promising avenue for real-time monitoring of organ donation awareness. This could potentially inform targeted campaigns and interventions that address regional needs or promote types of organ donation. However, the authors acknowledge limitations, including biases inherent to Twitter's user demographics, which may not represent the general population in terms of age, gender, and geographic distribution. [5]

W.B. Zulfikar et al., in their paper An Approach to Classify Eligibility Blood Donors Using Decision Tree and Naive Bayes Classifier (2018), proposed a model for classifying eligible blood donors through decision tree and Naive Bayes classifiers to streamline and enhance the efficiency of blood donor eligibility assessment. The study addresses a pressing issue faced by the Indonesian Red Cross (PMI): a shortage of safe blood supplies and the inefficiency of current manual eligibility assessments. Existing methods, such as contacting potential donors at random, often result in low eligibility rates due to mismatches with required health criteria (e.g., age, weight, blood pressure, and hemoglobin levels). The authors propose a solution using machine learning algorithms to systematically classify potential blood donors, thereby reducing the time and resources PMI invests in determining donor eligibility. The research utilizes both the decision tree and Naive Bayes classifiers to classify donors based on critical attributes like blood type, gender, age, blood pressure, and hemoglobin levels. In the decision tree method, the model builds a tree structure to classify donors by calculating entropy and gain values for each attribute, helping determine the most informative features at each step. For instance, the study shows gender as the highest gain value, making it the first node in the decision tree. The tree is expanded further, using age, blood type, blood pressure, and hemoglobin to create branching nodes, eventually reaching a comprehensive classification model for donor eligibility. The Naive Bayes classifier, on the other hand, is a probabilistic model that calculates the likelihood of donor eligibility by assessing the probability distributions of each attribute in relation to eligibility status. The model calculates the membership probabilities of each class (eligible or ineligible) based on attribute values and then compares these probabilities to determine the final classification. The results of the study indicate that the Naive Bayes classifier outperforms the decision tree in terms of accuracy and efficiency. [4]

Aydan Haka et al., in their paper "Comparative Evaluation of Mechanisms for Traffic Prioritization in LTE Networks" (2019), proposed a comparative analysis of different traffic prioritization mechanisms in LTE networks to determine the most effective approach for maintaining Quality of Service (QoS). The authors compare their own prioritization method against two others developed by Myo and Akyıldız, with the goal of assessing which mechanism best meets the complex QoS requirements in LTE networks. The paper addresses the growing demand for efficient data prioritization in LTE networks, which are essential in supporting high-bandwidth applications and IoT connections. As LTE networks continue to serve as a foundation for 5G technology, prioritizing traffic based on parameters like user mobility, QoS class, and service type has become critical for ensuring high-speed, reliable connections. The prioritization mechanisms discussed focus on optimizing the scheduling of e-Node B resources in LTE by factoring in criteria such as service type, user location, speed, and payment tier, which influence how bandwidth is allocated and which users get priority access. Haka and colleagues present their mechanism as an improvement over previous methods by adding prioritization criteria that extend beyond the standard LTE QoS requirements set by the 3GPP. Their mechanism prioritizes users based on the price paid for guaranteed service, proximity to the base station, mobility, and service type. By implementing a multi-layered approach, the authors aim to minimize service disruptions, especially for high-speed mobile users or those at the cell's edge who may otherwise face degraded service [2]

Absalom E. Ezugwu et al., in the paper, Computational Intelligence Approach to Dynamic Blood Allocation With ABO-Rhesus Factor Compatibility Under Real-World Scenario, (2020) proposed an advanced mathematical model and hybrid metaheuristic algorithm for optimizing blood bank operations. Their work addresses the challenges of managing blood supply chains, including perishability, stochastic demand, and compatibility constraints between blood types, especially with the ABO-Rhesus system. Efficient blood management is a critical challenge due to the perishability of blood products and the complexity of compatibility across ABO and Rhesus factors. The paper by Absalom E. Ezugwu et al. introduces a novel approach to these challenges by formulating a dynamic mathematical model that incorporates both ABO and Rhesus compatibility. It also proposes a hybrid metaheuristic algorithm combining symbiotic organisms search (SOS), genetic algorithms (GA), and particle swarm optimization (PSO), termed SOSGAPSO. The mathematical model extends an existing framework to include Rhesus factors, increasing the complexity of compatibility considerations from 4 blood types to 8. This enhanced model provides a more realistic representation of blood bank operations, allowing for better inventory planning, demand satisfaction, and reduction of wastage. The model is implemented using real-world data from the Nigerian National Blood Transfusion Service, providing practical relevance and validation. The hybrid

SOSGAPSO algorithm leverages the strengths of its constituent techniques. SOS contributes robust global search capabilities, GA ensures diversity through crossover and mutation, and PSO provides effective local optimization. Together, these algorithms address the NP-hard nature of the blood allocation problem, optimizing blood assignment while minimizing wastage and the need for external imports. The results of the study are compelling. Numerical experiments demonstrate that the proposed approach significantly improves blood allocation efficiency compared to traditional methods. [1]

Pinola Govender et al., in the paper A Symbiotic Organisms Search Algorithm for Optimal Allocation of Blood Products, (2018) proposed an advanced approach for addressing the blood assignment problem (BAP) in blood banks. This study is motivated by the need to reduce wastage due to blood product expiration and minimize the operational costs of importation, while ensuring effective allocation of blood to meet demand under compatibility constraints. Blood inventory management is a critical challenge due to the perishable nature of blood products, fluctuating supply, and stochastic demand. This study focuses on improving the efficiency of blood allocation systems using the Symbiotic Organisms Search (SOS) algorithm—a nature-inspired metaheuristic optimization approach. The authors introduced a mathematical model for the BAP that minimizes blood product wastage and operational costs by incorporating factors such as ABO-Rhesus compatibility, demand variability, and supply constraints. Unlike previous models that relied on generic datasets, this study implemented stochastic data generation methods based on South African demographic and behavioral statistics. This ensured realistic simulations of supply and demand trends. The SOS algorithm was hybridized with a robust blood assignment policy, introducing systematic processes for blood expiration management and dynamic reallocation of compatible blood types.[3]

III. Blood Compatibility Matching algorithm

The Blood Compatibility Matching Algorithm ensures safe blood transfusions by matching donor and recipient blood types based on the ABO and Rh factor systems. Compatibility depends on established medical guidelines: type O blood is universally compatible in the ABO system as a donor type, but recipients with type O can only receive type O blood. Type A can donate to A and AB types, type B can donate to B and AB types, and type AB is a universal recipient. Additionally, Rh compatibility is required: Rh positive recipients can receive from both Rh positive and Rh-negative donors, but Rh-negative recipients require Rh negative blood. Using a decision tree structure, the algorithm assesses ABO and Rh compatibility and outputs either a positive match (proceed with transfusion) or a negative match (deny transfusion), minimizing the risk of adverse transfusion reactions.

Algorithm design:
The algorithm makes use of a choice Tree approach, which offers an established and green technique for making compatibility decisions. This approach facilitates navigate compatibility policies through systematically checking every blood kind's trait and comparing them against acknowledged transfusion compatibility standards.

Inputs:
Donor’s Blood kind: facts on the ABO and Rh factor classification of the donor’s blood.
Recipient’s Blood type: information on the ABO and Rh thing category of the recipient’s blood.

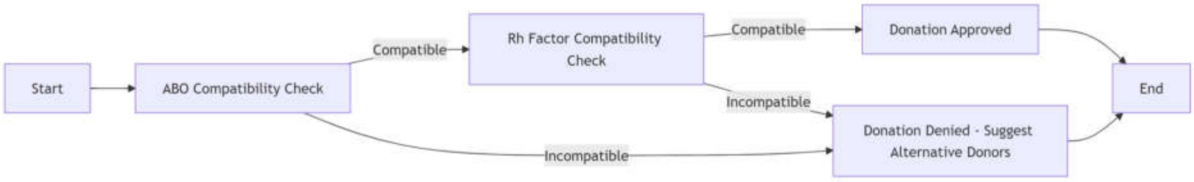

Fig. 01 Architecture of Blood Compatibility Matching algorithm

Working & Process:

1. Compatibility Matrix Reference:
The set of rules makes use of a predefined compatibility matrix based totally at the ABO and Rh blood organization systems to manual selection making. This matrix includes hooked up medical tips on which blood types are well matched for transfusion.

2. Selection Tree Execution:

The decision tree first assesses ABO compatibility: type O blood, which lacks A or B antigens, is universally compatible as a donor type inside the ABO gadget. but, recipients with type O blood can most effectively get hold of kind O, type A blood can donate to A and AB sorts., type B blood can donate to B and AB kinds, type AB blood can acquire from any ABO type (conventional recipient inside the ABO device).
Following ABO willpower, the algorithm assesses Rh factor compatibility: If the recipient has a fantastic Rh element, they can acquire blood from either Rh high quality or Rh poor donors. If the recipient has a poor Rh aspect, they could only receive Rh terrible blood.

3. Choice Output:

Compatible results: If each ABO and Rh elements align in line with the compatibility regulations, the set of rules returns a tremendous healthy, allowing the donation to continue. Incompatible outcome: If either ABO or Rh aspect compatibility is violated, the set of rules returns a terrible fit, denying the donation and probably suggesting alternative donors who meet the compatibility criteria.

Advantages

1. Improved Patient Safety: By ensuring that only compatible blood types are matched, the algorithm significantly reduces the risk of adverse transfusion reactions, which can lead to serious complications in patients.

2. Structured and Efficient Decision Making: The decision tree approach allows for systematic and quick checks against ABO and Rh compatibility rules, making it computationally efficient for binary classification decisions.

3. Universal Guidelines: The ABO and Rh compatibility rules are well documented and rarely change, making this algorithm highly stable and reliable over time without frequent updates.

4. Reduction of Manual Errors: Automated compatibility matching minimizes human error in blood type matching, improving accuracy and reliability in high stress medical settings where quick decisions are often needed.

5. Supports Large Scale Operations: With efficient processing, the algorithm can handle large volumes of compatibility checks in blood banks, making it scalable for widespread use in healthcare systems.

Disadvantages

1. Limited to ABO and Rh Factors: This algorithm does not account for less common antigens (e.g., Kell, Duffy, MNS) that may be relevant in certain cases, especially in patients who require frequent transfusions and may develop antibodies against these rarer antigens.

2. Rigidity in Critical Situations: In emergencies where universal donors (e.g., O negative) are unavailable, the algorithm does not provide alternative solutions beyond compatibility denial, which could limit its utility in urgent or rare situations where flexibility is needed.

3. Lacks Individualization: This approach does not consider individual patient conditions or unique medical histories, such as antibodies developed from prior transfusions, that may influence transfusion compatibility beyond standard ABO and Rh factors.

4. Potential Over Reliance on Algorithmic Decision: In some cases, healthcare providers may become too reliant on algorithmic outputs, which could reduce oversight or lead to unexamined assumptions, especially if atypical cases require more personalized assessments.

5. Not Adaptive to New Findings: Although stable, the algorithm may need updating if new findings in blood compatibility emerge. Adapting it for additional compatibility factors would require a redesign of the decision tree and could increase complexity and processing time.

Limitations:

1. The algorithm is predicated on a confined set of compatibility factors (ABO and Rh). at the same time as good enough for maximum cases, it can no longer account for rarer antigen profiles or person recipient conditions.
2. In emergencies in which prevalent donors (Obad) are unavailable, the algorithm does not provide solutions past compatibility denial, which can limit software in vital situations.

Applications:

- **Blood Bank Management:** Ensures that each blood donation is safely matched with compatible recipients, reducing the risk of transfusion reactions.
- **Emergency Room and Trauma Centers:** Provides quick compatibility decisions during emergencies, helping clinicians select compatible blood types rapidly for trauma patients.
- **Surgical Support:** Used in preoperative planning to confirm that compatible blood is available for surgeries where blood transfusions may be necessary.
- **Oncology and Chronic Care:** Ensures safe blood compatibility for patients requiring frequent transfusions, such as those undergoing chemotherapy or with chronic blood disorders (e.g., sickle cell anemia, thalassemia).
- **Automated Transfusion Systems:** In automated systems within hospitals, this algorithm could work as a safety check to verify blood compatibility before the transfusion process begins.

IV. Donor Eligibility Algorithm

The Donor Eligibility Algorithm evaluates whether potential donors meet health and eligibility criteria, ensuring donor and recipient safety. It combines a rule-based system with a Support Vector Machine (SVM) model to assess straightforward eligibility factors and more complex health metrics. Initial rule-based checks verify essential criteria like age, weight, and donation frequency, quickly identifying ineligible donors. For those who meet basic standards, the SVM model evaluates advanced metrics (e.g., hemoglobin levels, blood pressure), where health indicators interact nonlinearly. The SVM model classifies donors as eligible or ineligible, relying on patterns learned from past data. If both checks are passed, the donor is approved; otherwise, they are advised to reapply once they meet eligibility requirements. The combined approach ensures a thorough screening process, supporting high standards for blood supply quality.

Algorithm Design

The algorithm combines a Rule-primarily based device with a guide Vector device (SVM) model:

- Rule-primarily based system: Implements straightforward eligibility assessments based on nicely-described health standards and donation frequency.
- Help Vector device (SVM): Assesses extra complex health factors and allows categorize donors as eligible or ineligible based on health metrics which can engage in nonlinear ways.

Inputs

- Final Donation Date: The time elapsed because donor's remaining donation.
- Fitness Metrics: Donor's age, weight, hemoglobin stages, and different health indicators as required by donation standards.

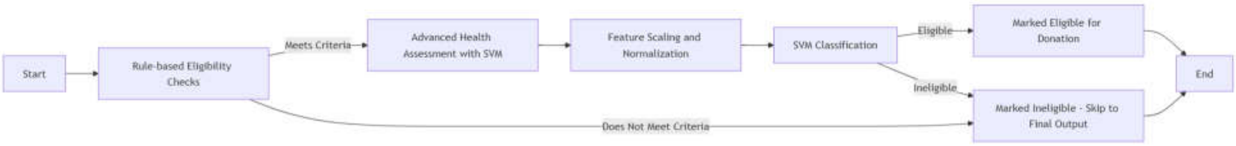

Fig. 02 Architecture of Donor Eligibility Matching algorithm

Working & Process

1. Rule-based totally Eligibility looks at:

The set of rules first runs each donor's facts thru a fixed of predefined guidelines. as an example: Donation Frequency: The donor should have a gap of as a minimum three months because remaining complete blood donation. Minimal fitness standards: basic health requirements (e.g., age and weight thresholds) should be met (e.g., the donor must be over 18 years antique and weigh above a certain minimal). If a donor does no longer meet these fundamental criteria, they may be straight away marked ineligible, and the algorithm skips to the final output.

2. Superior fitness assessment with SVM:

If the donor meets primary standards, the algorithm then applies SVM to evaluate extra complicated health metrics. The SVM version takes in inputs consisting of hemoglobin degrees, blood stress, and potentially different fitness signs that may not in shape simple regulations however effect eligibility. Characteristic Scaling and Normalization: earlier than processing, the fitness information is scaled and normalized to improve SVM's performance. Classification: SVM classifies the donor as "eligible" or "ineligible" based on the trained model, which has been adjusted the usage of beyond donor facts to understand patterns that imply secure and appropriate donors.

3. Selection Output:

Eligible: If both rules based totally assessments and SVM class deem the donor suitable, they are marked as eligible for donation. Ineligible: If both the rule of thumb-based exams or SVM classification flag any issues, the donor is marked ineligible.

Advantages

1. Comprehensive Assessment: By combining a rule-based system with an SVM (Support Vector Machine) model, the algorithm provides a thorough evaluation of potential donors. Basic eligibility is first checked against well-defined criteria, and advanced health metrics are evaluated to ensure the safety and suitability of each donor.

2. Improved Safety Standards: The dual layer approach helps maintain high safety standards by screening out donors who may pose health risks to recipients or themselves. This prevents potential adverse reactions and contributes to a safer blood supply.

3. Efficient Screening Process: The rule-based component quickly filters out ineligible candidates based on straightforward criteria (e.g., age, weight, donation frequency), saving time by focusing computational resources on more complex cases only when needed.

4. Adaptability to Nonlinear Relationships: The SVM model is well-suited for handling nonlinear relationships between health metrics, such as blood pressure, hemoglobin levels, and other indicators that influence donor eligibility. This improves the algorithm's ability to identify eligible donors even when complex health factors are involved.

5. Scalable for Large Databases: The algorithm can handle many donor records, making it suitable for busy blood banks that need to screen numerous donors daily.

Disadvantages

1. Frequent Updates Required: The SVM model may need frequent retraining as new health standards and eligibility requirements emerge. Additionally, the rule-based component requires periodic updates to reflect current medical guidelines, adding maintenance complexity.

2. Imbalanced Data Sensitivity: The SVM model may perform less accurately if trained on imbalanced data—where eligible cases significantly outnumber ineligible ones. This could lead to a higher risk of false negatives (incorrectly classifying eligible donors as ineligible) or false positives (allowing ineligible donors).

3. Potential Overreliance on Algorithmic Output: Healthcare professionals may rely too heavily on the algorithm's output, which could reduce manual oversight in borderline cases where human judgment might be necessary to assess eligibility accurately.

4. Data Quality Dependency: The algorithm's accuracy heavily depends on the quality of the input health data. Inaccurate or inconsistent data (e.g., incorrect health metrics) may reduce the reliability of eligibility assessments, which could lead to incorrect eligibility decisions.

5. Computational Complexity of SVM: SVM models can be computationally intensive and slow when processing large, high dimensional datasets, especially as additional health metrics are incorporated. This could impact processing speed if the system experiences a high volume of simultaneous donor screenings.

Limitations

1. The SVM model can also require common updates as new health requirements emerge, and it can be impacted through imbalanced facts if there are notably fewer ineligible instances in the schooling set.

2. SVM's performance can range based on records nice; if fitness data is inconsistent or erroneous, eligibility exams can be less reliable.

Applications:

- **Blood Donor Screening:** Automates the screening process in blood donation centers, ensuring only eligible donors proceed, improving both donor and recipient safety.
- **Mobile Blood Drives:** Used in mobile donation setups to quickly assess donor eligibility onsite, allowing immediate approval or denial based on health metrics and donation history.
- **Donor Database Management:** Regularly assesses a donor database to identify suitable candidates for donation, especially useful in encouraging past donors to donate again when eligible.
- **Hospital Pre-Screening:** In hospitals, this algorithm could support prescreening for potential donors among family members in cases where directed donations are needed.
- **Public Health Programs:** Assists government and nonprofit organizations in maintaining a safe donor pool by identifying and retaining healthy, eligible donors in their blood donation programs.

V. CONCLUSION

This paper presents three critical algorithms in the context of blood transfusion management, focusing on Blood Compatibility Matching, Request Prioritization, and Donor Eligibility. Each algorithm is designed to improve the efficiency and safety of blood donation and transfusion processes, addressing various operational challenges in blood banks. The Blood Compatibility Matching Algorithm ensures safe blood transfusions by matching the blood type of the donor and recipient based on the ABO blood group system and the Rh factor. It uses a decision tree structure to navigate through compatibility rules, providing binary outcomes for compatibility—either approving or denying the transfusion. This algorithm efficiently supports medical decision-making but is limited by its focus on ABO and Rh compatibility and its inability to address rare antigen profiles. The Donor Eligibility Algorithm assesses the suitability of potential blood donors by evaluating health metrics and donation history. It combines a rule-based system for basic health checks with a Support Vector Machine (SVM) for more complex health evaluations. The algorithm outputs a binary decision of eligibility, ensuring that only safe donors are approved. While the SVM model can handle complex health data, its performance may be affected by data quality and the need for regular updates as health standards evolve. Together, these algorithms offer a robust framework for managing blood donation and transfusion processes, optimizing safety and resource allocation while acknowledging the need for continuous refinement to handle emerging challenges.

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