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ORIGINAL RESEARCH

Machine Learning Models for Predicting the Need for Early Packed Red Blood Cell Transfusion in Multiple Trauma Patients

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Abstract: **Introduction:** One of the preventable contributors to trauma mortality is hemorrhagic shock, which requires early recognition and immediate intervention. In this retrospective analysis, we aimed to develop and optimize machine learning (ML) algorithms to predict the need for packed red blood cell (PRBC) transfusion within 24 hours of injury in multiple trauma patients. **Methods:** This retrospective longitudinal study analyzed consecutive multiple trauma patients admitted to the emergency department. The outcome was transfusion of at least one unit of PRBC within the first 24 hours of traumatic injury. SHAP analysis was employed for feature selection, and the five key predictors were identified and entered in the models: Glasgow Coma Scale (GCS), hemoglobin (Hb), pulse rate (PR), systolic blood pressure (SBP), and pulse pressure. The dataset was split 80:20 for training/testing, and multiple machine learning algorithms were evaluated based on area under the receiver operating characteristic curve (AUC), F1 score, sensitivity, specificity, positive predictive value (PPV), and negative predictive value (NPV). **Results:** The study cohort consisted of 908 patients, with a median age of 34 years. PRBC transfusions were more common in older adults with lower GCS scores, higher PR, lower SBP, lower pulse pressure, and lower Hb levels on admission. Among the machine learning models, Random Forest performed best (AUC: 0.997, sensitivity: 0.938, specificity: 0.994), followed by K-Nearest Neighbors and Logistic Regression, both of which showed perfect specificity but lower sensitivity. **Conclusion:** Random Forest outperformed other ML algorithms, achieving high discriminative ability, sensitivity, and specificity. PR, GCS, Hb, SBP, and pulse pressure were the most influential predictors of the need for early transfusion. Despite promising results, further multicenter validation studies are needed to confirm the real-world applicability of these models.

Keywords: Mathematical model; Machine learning; Wounds and injuries; Glasgow coma scale

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1. Introduction

Globally, trauma is the sixth leading cause of death, accounting for 9% of mortalities worldwide, and it is considered the second leading cause of death in Iran (1, 2). These fatalities predominantly occur within the first 12 hours following injury (3). One of the most critical and preventable contributors to trauma mortality is hemorrhagic shock, which requires early recognition and immediate intervention with fluid resuscitation and packed red blood cell (PRBC) transfusion (4-6). Studies indicate that early administration of PRBCs—particularly within the first 15 minutes after injury—reduces both 24-hour mortality (5.6% vs. 20.2%) and 30-day mortality (11.8% vs. 22.9%) compared to delayed or absent transfusion (7). Conversely, delayed transfusion increases the risk of pulmonary complications and mortality

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(8).
Several scoring systems have been developed to predict massive transfusion in both military and civilian trauma patients (9-11). However, with advancements in pre-hospital and hospital trauma care, the need for massive transfusions has declined (10), and less attention has been given to predicting massive blood transfusions, despite their critical role in patient stabilization. The fifth edition of the European Trauma Guidelines recommends maintaining hemoglobin (Hb) between 7-9 g/dl (6), yet initial Hb values can be misleading, as they may appear normal despite ongoing hemorrhage.
In a previous study, we evaluated the diagnostic accuracy of various scoring systems for predicting PRBC transfusion in multiple trauma patients (12). However, given the limitations of traditional clinical judgment and scoring systems, machine learning (ML) models have emerged as a promising alternative for improving transfusion decision-making. Unlike rigid scoring systems, ML algorithms can dynamically integrate multiple clinical variables, offering more accurate and timely predictions. Therefore, the aim of the current study was to evaluate the accuracy of ML predictive models in determining the need for PRBC transfusion within the first 24 hours of injury in multiple trauma patients.

2. Methods

2.1. Study design and setting

The present retrospective longitudinal study analyzed consecutive multiple trauma patients admitted to the emergency department (ED) at Shohadaye Tajrish Hospital, Tehran, Iran, from March to September 2023. The hospital is a level 1 trauma center, where blood transfusion decisions are made by attending surgeons and emergency medicine specialists based on clinical and laboratory evaluations. The dataset used in this study was previously analyzed in a separate publication (12). Ethical approval was granted by Shahid Beheshti University of Medical Sciences (IR.SBMU.TEB.POLICE.REC.1402.046). Due to the retrospective nature of the study, informed consent was waived. The study aimed to predict the need for PRBC transfusion within the first 24 hours of traumatic injury.

2.2. Participants

The inclusion criteria encompassed adults (>18 years old) diagnosed with multiple trauma (ICD-10 coded). Patients who were dead on arrival or discharged from the ED without admission were excluded, as they were unlikely to receive transfusions. Additional exclusion criteria included age below 18 years, pregnancy, and patients leaving against medical advice.

2.3. Data preprocessing

The analyses were conducted using Python 3.11.1 with the following libraries: scikit-learn (for model training and evaluation), SHAP (for feature interpretation), XGBoost (for initial feature selection), and Matplotlib and Seaborn (for visualization). All computations were performed on a standard personal computer, without GPU acceleration or cloud computing.
Normalization was performed using Python's StandardScaler to transform dataset features so that they have a mean of 0 and a standard deviation of 1. This step ensures each feature contributes equally to the analysis, enhancing the performance of machine learning models. By applying this transformation, the dataset is adjusted to a consistent scale without distorting the differences between values, thereby improving the reliability of the machine learning analysis.
A total of 996 patients were initially included. The following preprocessing steps were applied to ensure data quality:
Patients with missing Focused Assessment Sonography in Trauma (FAST) results were removed (leaving 908 patients). Missing values in venous blood gas (pH, PCO_2, HCO_3, base deficit) and complete blood count (hemoglobin, hematocrit) were imputed using multivariate linear regression involving all other predictor variables. One-hot encoding was applied to categorical variables. No balancing techniques (e.g., SMOTE, oversampling) were applied to preserve the original data distribution.

2.4. Feature selection

To determine the most important predictors for PRBC transfusion, a preliminary XGBoost model was trained using all 33 candidate features. These features included demographic variables (e.g., gender, age), clinical variables (e.g., vital signs, mechanism of injury, trauma type, method of transportation to the hospital, Glasgow Coma Scale (GCS), norepinephrine administration, tranexamic acid administration, intubation, FAST findings, and medication history), and laboratory variables (e.g., hemoglobin levels and venous blood gas biomarkers such as pH, PCO_2, HCO_3, and base deficit) at the time of ED admission. SHAP (Shapley Additive Explanations) was then applied to assess feature importance, and the five most influential features were selected: GCS, Hb, Pulse Rate (PR), Systolic Blood Pressure (SBP), and Pulse Pressure (Figure 1). These five features were used in subsequent machine learning models to predict the need for PRBC transfusion.

2.5. Machine learning models

Six supervised learning models were trained using the five selected features: K-Nearest Neighbors (KNN) (n_neighbors=3), Support Vector Machine (SVM) (linear kernel, probability=True), Logistic Regression, Decision Tree (max_depth=5), Neural Network (MLP) (5 hidden units, max_iter=500), and Random Forest (n_estimators=50, max_depth=5). The dataset was split into training (80%) and testing (20%) sets using stratified random sampling. Model hyperparameters were kept consistent across runs.

2.6. Performance evaluation

Each model's performance was assessed using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC). Additional performance metrics included Sensitivity (Recall), Specificity, Positive Predictive Value (PPV), Negative Predictive Value (NPV), and F1-score. To compute 95% confidence intervals (CIs) for these metrics, a bootstrapping approach (n=200 resamples) was used. To explain the model's decision-making process, SHAP analysis was applied to the best-performing model (Random Forest).

3. Results

3.1. Patient characteristics

Table 1 shows the characteristics of the included patients. A total of 908 trauma patients were included in the analysis after data preprocessing. The mean age was 37.38 ± 16.11 (range: 18 - 96) years, and 71.9% were male, 726 were allocated to the training set and 182 to the test set. Most patients (94%) were blunt trauma cases.

Of the 908 patients, 78 (8.59%) were transfused at least one unit of PRBCs in the first 24 hours of their arrival to ED, 25 (2.75%) needed massive transfusion, 32 (3.52%) needed platelet transfusion, and 39 (4.30%) needed FFP transfusion. The mortality rate of the study population was 3.41% (n = 31). There were significant differences between the transfusion group and non-transfusion group in age ($p = 0.0001$), type of trauma ($p < 0.001$), mode of transportation to hospital ($p < 0.001$), GCS ($p = 0.0001$), norepinephrine administration in ED ($p < 0.001$), prehospital or ED intubation ($p < 0.001$), positive findings in FAST ($p < 0.001$), and medication history of anti-platelet ($p = 0.019$) and anti-coagulant ($p = 0.018$) drugs. There were no significant differences between the transfusion group and the non-transfusion group in gender ($p = 0.444$), mechanism of injury (i.e. blunt or penetrating) ($p = 0.337$), and tranexamic acid administration in ED ($p = 0.086$) (Table 1). Only 25 (2.75%) patients underwent massive transfusion.

3.2. Model performance

The predictive accuracy of six supervised machine learning models was evaluated. The Random Forest model achieved the highest performance, with an AUC of 0.997, followed by KNN (0.995), Neural Network (0.989), Logistic Regression (0.992), SVM (0.984), and Decision Tree (0.962). In terms of sensitivity, Random Forest achieved the highest value (0.938, 95% CI: 0.818–1.000), followed by Logistic Regression and Neural Network (both at 0.812). Specificity remained high across all models, with KNN, SVM, and Logistic Regression achieving 100% specificity, while Random Forest and Neural Network reached 99.4% specificity. PPVs were highest for KNN, SVM, and Logistic Regression (1.000, 95% CI: 1.000–1.000), while Random Forest had a PPV of 0.938 (95% CI: 0.800–1.000). NPVs were similarly high, with Random Forest achieving 0.994 (95% CI: 0.982–1.000) and other models ranging between 0.971 and 0.982. The complete performance metrics for all models are presented in Table 1.

Figure 2 presents the ROC curves for all models, illustrating their discriminative ability. The Random Forest and KNN models exhibited nearly perfect discrimination, with AUC values of 0.997 and 0.995, respectively, while other models had AUCs ranging from 0.962 to 0.992.

3.3. Feature importance analysis (SHAP)

To further interpret the predictions of the best-performing model (Random Forest), SHAP analysis was conducted to determine the importance of each predictor variable. The five most influential predictors in the model were GCS, Hb, PR, SBP, and pulse pressure. The SHAP summary plot (Figure 3) highlights the relative impact of each variable, with Pulse Rate and GCS showing the highest influence on PRBC transfusion predictions. Additionally, the SHAP feature importance plot (Figure 4) ranks variables based on their mean absolute SHAP values.

4. Discussion

In this study, we developed and evaluated several machine learning models to predict the need for PRBC transfusion within the first 24 hours of trauma care. Our findings demonstrate that Random Forest achieved the highest predictive performance, outperforming other models, including KNN, SVM, Logistic Regression, Decision Tree, and Neural Network. Similar findings were reported by other similar studies by our team, where ensemble machine learning models, particularly Random Forest and XGBoost, outperformed others in trauma-related prediction tasks (13, 14). The five most influential predictors identified through SHAP analysis were PR, GCS, Hb, SBP, and pulse pressure.

The identification of vital signs and hemoglobin levels as critical predictors aligns with clinical expectations and underscores their role in assessing hemorrhagic risk. For instance, a low initial hemoglobin level observed soon after injury is usually an indicator of serious ongoing hemorrhage and has important implications for management and prognosis (15). Additionally, vital signs such as heart rate and blood pressure are essential in evaluating the severity of hemorrhagic shock. The Shock Index, which is the ratio of heart rate to systolic blood pressure, has been associated with predicting transfusion needs in trauma patients (16). Feng et al. also identified the importance of vital signs and hemoglobin levels in their prediction models (17). Their study used XGBoost and found hematocrit to be a critical variable, which aligns with our findings on Hb. They demonstrated that non-invasive parameters (e.g., shock index and systolic blood pressure) provided valuable information for predicting transfusion needs. These findings highlight the potential of machine learning models to enhance decision-making processes in trauma care by integrating these critical variables.

Importantly, during the study period, 163 PRBC reservations were made, yet only 78 patients required transfusion, leading to 85 unnecessary reservations (false positive rate of 10.2%). Implementing ML-based decision support tools could significantly reduce unnecessary PRBC reservations, thereby conserving valuable blood resources. By integrating these models into clinical workflows, healthcare providers can make more informed and timely decisions regarding transfusion needs.

Traditional scoring systems, such as the Assessment of Blood Consumption (ABC) score, have been utilized to predict massive transfusion requirements. However, these models often exhibit limitations in sensitivity and specificity. For instance, the ABC score, with a cutoff of ≥2, demonstrated a specificity of 94% and a sensitivity of 38% in predicting transfusion needs (18). In contrast, our Random Forest model achieved superior predictive performance. This aligns with findings from a systematic review, which identified 25 ML models developed to predict blood transfusion requirements after injury, with 17 demonstrating good to excellent performance (19).

We have previously assessed various scoring systems for predicting blood transfusion needs in trauma patients. In that study, we compared traditional scoring systems, such as the TASH score, ABC, GCS, and others, for predicting PRBC transfusions in multiple trauma patients. The TASH score, at a cutoff of ≥8.5, demonstrated a sensitivity of 84.4% and a specificity of 78.4% in predicting PRBC transfusion requirements (12). In comparison, the Random Forest model in the current study showed superior predictive performance, highlighting the enhanced accuracy of machine learning approaches over traditional scoring systems.

5. Limitations and future directions

As a single-center study, external validation is imperative to ensure the generalizability of our findings. Different hospitals with varying patient demographics and treatment protocols may yield different outcomes when applying these models. External validation would provide a more holistic understanding of the models' performance across diverse clinical environments. Future research should focus on multi-center studies to validate our results and other ML prediction models. Additionally, investigating the integration of these ML models into real-time clinical decision support systems could pave the way for their practical application. Further studies might also explore incorporating additional variables, such as genetic markers or detailed hemodynamic parameters, which could potentially enhance the predictive accuracy of the models.

6. Conclusions

The application of machine learning models in trauma care has the potential to transform the current paradigm of blood transfusion prediction. Our study provides a foundation for future research and development in this field, emphasizing the need for external validation and continuous refinement of ML models to meet the dynamic needs of trauma care.

7. Declarations

7.1. Acknowledgments

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7.2. Author contributions

SS and MY designed, conceptualized, and supervised the study. KZ, HZ, and NS collected the data. HZ and MY performed the data analysis and visualized the results. HZ, MY, SS, AS, and MV interpreted the results. HZ, NS and MV prepared the draft of the manuscript. All authors critically revised and approved the final manuscript.

7.3. Funding

This study was not funded and did not receive any grants.

7.4. Competing interests

The authors declare that there are no conflicts of interest.

7.5. Ethics approval and consent to participate

Given the retrospective design of this study, the requirement for informed consent was waived in accordance with applicable ethical guidelines. All data were anonymized to ensure the protection of participant confidentiality.

7.6. Availability of data and materials

The data and codes from this study will be available upon reasonable request from the corresponding authors.

7.7. Using artificial intelligence chatbots

None.

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Table 1: Study population characteristics (n = 908 patients)

Characteristics	Total	Need for PRBC transfusion		P-value
		No (n= 830)	Yes (n = 78)	
Gender				
Male, n (%)	653 (71.92)	594 (71.57)	59 (75.64)	0.444†
Age (year)				
Median (IQR)	34 (25-44.5)	33 (24-43)	43 (29-60)	0.0001*
Mechanism of injury				
Blunt	850 (93.61)	775 (93.37)	75 (96.15)	0.337†
Penetrating	58 (6.39)	55 (6.63)	3 (3.85)	
Type of trauma, n (%)				
Motorcycle	278 (30.62)	264 (31.81)	14 (17.95)	< 0.001†
Car crash	216 (23.79)	193 (23.25)	23 (29.49)	
Fall < 3m	135 (14.87)	131 (15.78)	4 (5.13)	
Assault	106 (11.67)	104 (12.53)	2 (2.56)	
Pedestrian to car	86 (9.47)	71 (8.55)	15 (19.23)	
Pedestrian to motorcycle	39 (4.30)	37 (4.46)	2 (2.56)	
Fall > 3m	34 (3.74)	21 (2.53)	13 (16.67)	
Others	14 (1.54)	9 (1.08)	5 (6.41)	
Transport to hospital, n (%)				
EMS	612 (67.40)	567 (68.31)	45 (57.69)	< 0.001†
Patient came by himself	245 (26.98)	241 (29.04)	4 (5.31)	
Referred from another hospital	51 (5.62)	22 (2.65)	29 (37.18)	
Vital signs, median (IQR)				
HR	82 (78-87)	82 (78-86)	122 (100-130)	< 0.0001*
SBP	120 (110-128)	120 (110-130)	100 (87-109)	< 0.0001*
DBP	75 (70-80)	75 (70-80)	60 (50-70)	< 0.0001*
RR	16 (16-18)	16 (16-18)	18 (10-26)	0.100
Pulse pressure	45 (40-50)	45 (40-50)	40 (35-45)	< 0.0001*
GCS, n (%)				
13-15	859 (94.60)	826 (99.52)	33 (42.31)	0.0001‡
9-12	17 (1.87)	1 (0.12)	16 (20.51)	
3-8	32 (3.52)	3 (0.36)	29 (37.18)	
Laboratory data, median (IQR)				
Hb	14.1 (12.6-15.3)	14.3 (13.0-15.4)	10.8 (9.5-11.8)	< 0.0001*
Hct	41.9 (37.9-45.1)	42.4 (39.3-45.2)	32.2 (28.2-35.3)	< 0.0001*
pH	7.38 (7.35-7.40)	7.38 (7.36-7.41)	7.29 (7.21-7.33)	< 0.0001*
HCO_3	24.1 (22.3-25.6)	24.3 (23.0-25.8)	18.25 (14.4-21.4)	< 0.0001*
PCO_2	42.7 (38.5-46.4)	42.8 (38.7-46.2)	42.05 (36.5-48.3)	0.801
Base deficit	-0.8 (-2.5, +0.5)	-0.6 (-1.9, +0.7)	-6.05 (-7.8, -3.3)	< 0.0001*
Norepinephrine administration in ED, n (%)				
Yes	37 (4.07)	0 (0.00)	37 (47.44)	< 0.001§
Tranexamic acid administration in ED, n (%)				
Yes	1 (0.11)	0 (0.00)	1 (1.28)	0.086§
Prehospital or ED intubation, n (%)				
Yes	38 (4.19)	3 (0.36)	35 (44.87)	< 0.001§
Positive findings in FAST, n (%)				
Yes	30 (3.30)	1 (0.12)	29 (37.18)	< 0.001§
Medication history, n (%)				
Anti-platelet drugs	41 (4.52)	33 (3.98)	8 (10.26)	0.019§
Anti-coagulant drugs	19 (2.09)	14 (1.69)	5 (6.41)	0.018§
Prediction scores for transfusion, n (%)				
TASH score ≥ 16	24/569 (4.22)	0/491 (0.00)	24/78 (30.77)	< 0.001§
ABC score ≥ 2	31/908 (3.41)	0/830 (0.00)	31 (39.74)	< 0.001§
Shock Index ≥ 1	59/908 (6.50)	5/830 (0.60)	54/78 (69.23)	< 0.001†

IQR: interquartile range; Hb: hemoglobin; Hct: hematocrit; EMS: emergency medical service; HR: heart rate; SBP: systolic blood pressure; DBP: diastolic blood pressure; RR: respiratory rate; GCS: Glasgow coma scale; ED: emergency department; FAST: focused assessment with sonography in trauma; ABC: assessment of blood consumption; TASH: trauma associated severe hemorrhage; PRBC: packed red blood cell. * Mann–Whitney U test; † Pearson X^2; ‡Kruskal-Wallis; §Fisher's exact test.

Table 2: The performance of the six machine learning models in prediction of the need for PRBC transfusion in 908 multiple-trauma patients

Model	AUC	Sensitivity	Specificity	PPV	NPV	F1 Score
KNN	0.995	0.687 (0.467 - 0.895)	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)	0.971 (0.942 - 0.990)	0.815 (0.815 - 0.815)
SVM	0.984	0.750 (0.533 - 0.939)	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)	0.976 (0.949 - 0.995)	0.857 (0.857 - 0.857)
Logistic Regression	0.992	0.812 (0.610 - 1.000)	1.000 (1.000 - 1.000)	1.000 (1.000 - 1.000)	0.982 (0.959 - 1.000)	0.897 (0.897 - 0.897)
Decision Tree	0.962	0.750 (0.533 - 0.941)	0.994 (0.982 - 1.000)	0.923 (0.786 - 1.000)	0.976 (0.951 - 0.995)	0.828 (0.828 - 0.828)
Neural Network	0.989	0.812 (0.583 - 1.000)	0.994 (0.976 - 1.000)	0.929 (0.764 - 1.000)	0.982 (0.960 - 1.000)	0.867 (0.867 - 0.867)
Random Forest	0.997	0.938 (0.818 - 1.000)	0.994 (0.982 - 1.000)	0.938 (0.800 - 1.000)	0.994 (0.982 - 1.000)	0.938 (0.938 - 0.938)

All measures are presented with 95% confidence interval. PRBC: packed red blood cell; AUC: area under the curve; PPV: positive predictive value; NPV: negative predictive value; KNN: K-nearest neighbors; SVM: support vector machine.

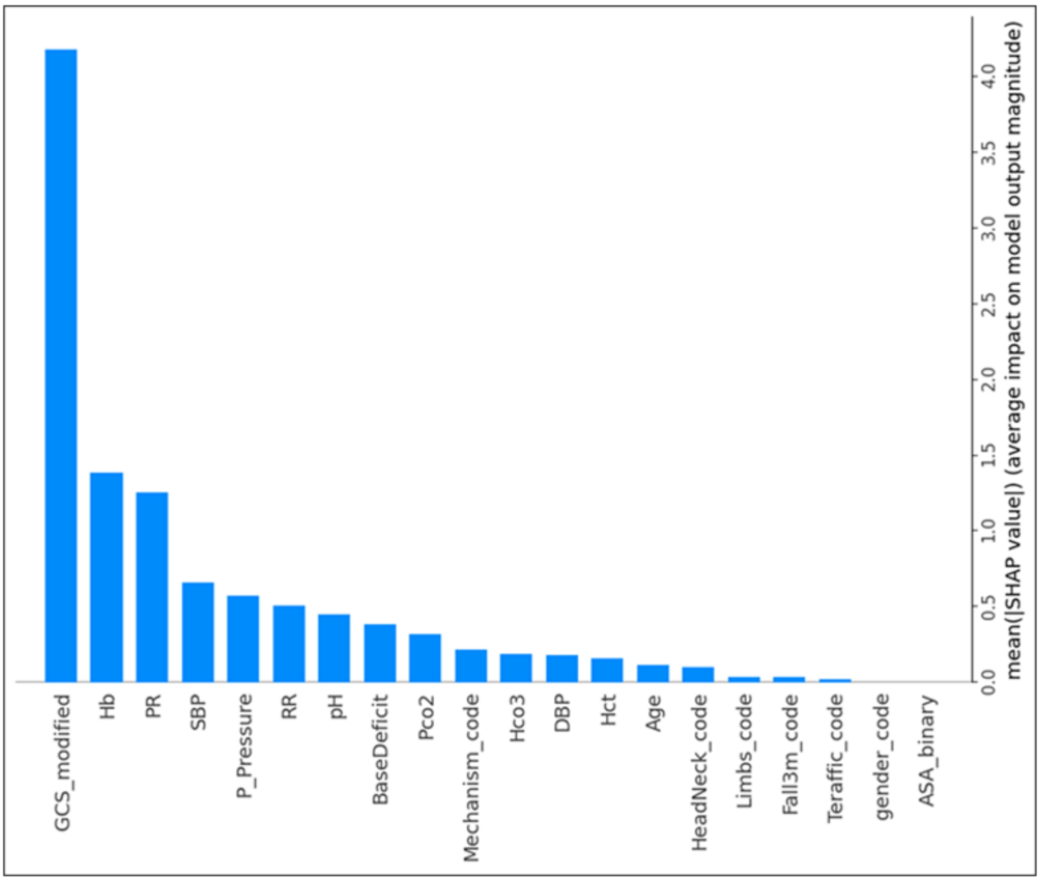

Figure 1: Feature importance analysis using SHAP from an initial XGBoost model. This figure illustrates the SHAP (Shapley Additive Explanations) feature importance ranking derived from an initial XGBoost model trained on 33 predictor variables. The horizontal bars represent the mean absolute SHAP values, indicating the average impact of each feature on the model's output. Features with higher SHAP values exert a stronger influence on predicting the need for packed red blood cell (PRBC) transfusion within the first 24 hours of injury. Based on this analysis, the five most important predictors (Glasgow Coma Scale (GCS), hemoglobin (Hb), pulse rate (PR), systolic blood pressure (SBP), and pulse pressure) were selected for subsequent machine learning model development.

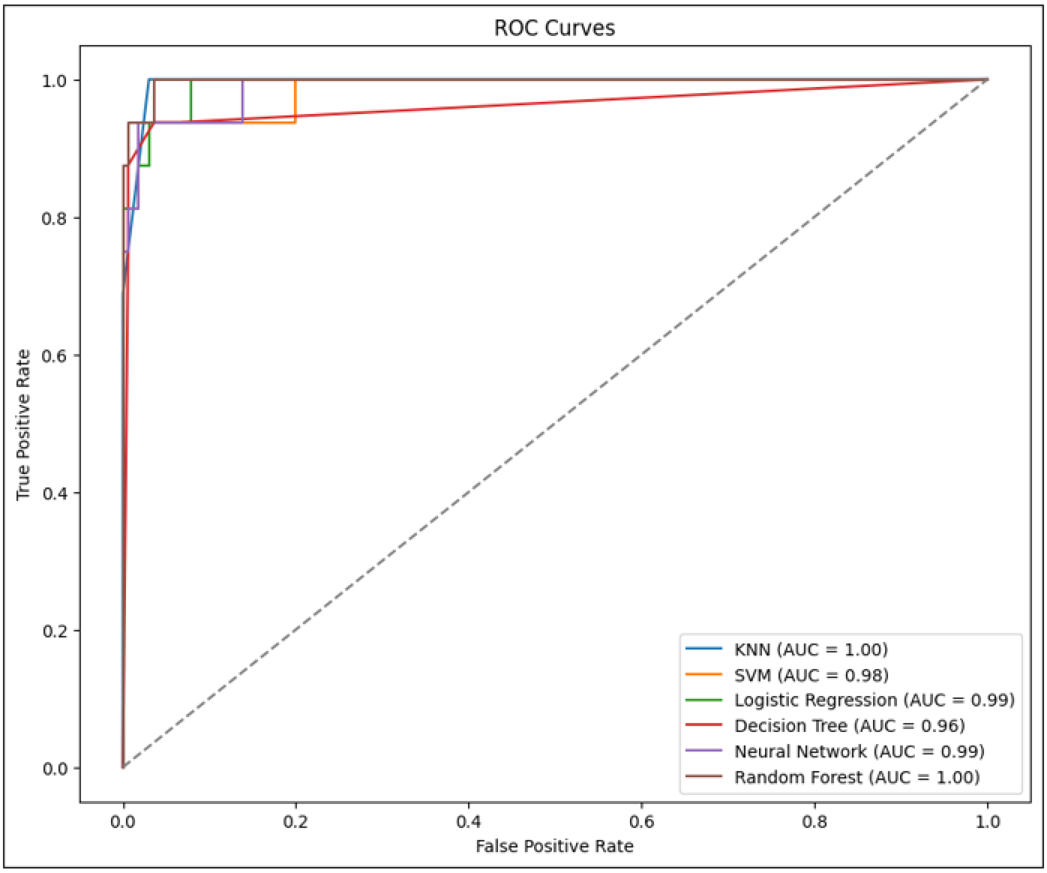

Figure 2: Receiver operating characteristic (ROC) curves for machine learning models predicting PRBC transfusion. The ROC curves illustrate the performance of the six machine learning models in predicting PRBC transfusion within 24 hours of injury. All models achieved near-perfect area under the curve (AUC) values. KNN: K-nearest neighbors; SVM: support vector machine.

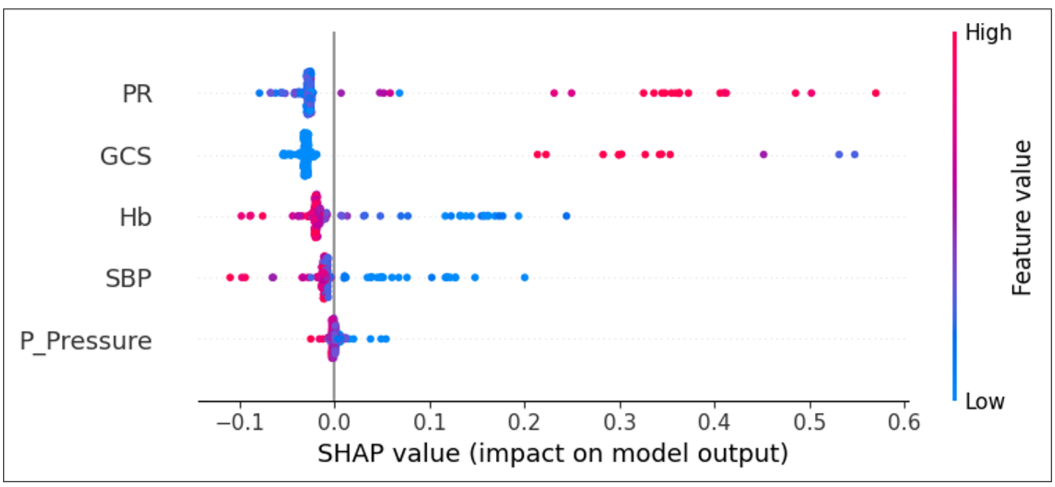

Figure 3: SHAP summary plot for packed red blood cell (PRBC) transfusion prediction. This summary plot illustrates the impact of the top five predictor variables (Glasgow come scale (GCS), hemoglobin (Hb), pulse rate (PR), systolic blood pressure (SBP), and Pulse Pressure) on the Random Forest model's output. Each point represents an individual patient, with the color gradient indicating the feature value (blue = low values, red = high values). Features positioned higher in the plot have a greater overall influence on the model's prediction. The horizontal spread of points shows the range of SHAP values, reflecting how much a particular feature increases or decreases the likelihood of PRBC transfusion within the first 24 hours of injury.

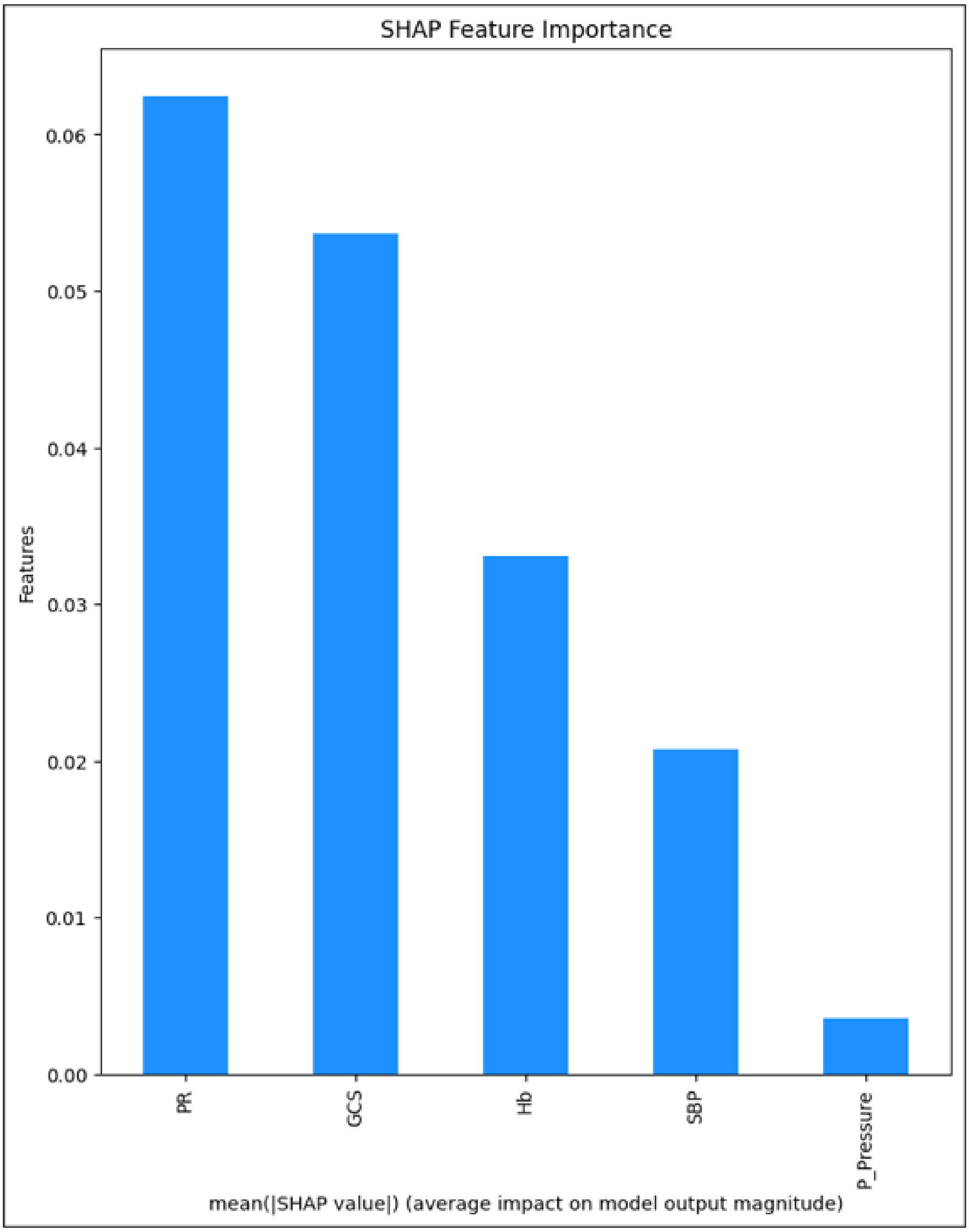

Figure 4: SHAP feature importance for packed red blood cell (PRBC) transfusion prediction. This bar chart represents the mean absolute SHAP values for the top five predictor variables, indicating their overall contribution to the Random Forest model's predictions of PRBC transfusion within 24 hours of injury. Features with higher SHAP values have a greater influence on model decisions. Pulse Rate (PR) and Glasgow Coma Scale (GCS) were the strongest predictors, followed by Hemoglobin (Hb), Systolic Blood Pressure (SBP), and Pulse Pressure (P_Pressure).