Blood Transfusion success rate prediction using Artificial Intelligence

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Abstract - Surgery has made extensive use of red blood cell (RBC) transfusion therapy, which has resulted in excellent treatment outcomes. However, doctors sometimes use their experience to determine whether or not RBC transfusions are necessary. In this study, we use machine learning models to predict whether a patient will require an intraoperative blood transfusion of red blood cells (RBCs) during mitral valve surgery. In surgery, blood transfusions are frequently used. The majority of blood products are used in cardiac surgery, where the rate of blood transfusions ranges from 40% to 90% (1-3). However, this treatment has advantages and disadvantages. In critically ill patients, transfusion has been linked to high rates of morbidity and mortality (4). Blood transfusion has been linked in some recent studies to worse outcomes, such as an increased risk of renal failure and infection and respiratory, circulatory, and neurological complications following cardiac surgery (5,6). Red blood cell (RBC) transfusion is linked to an increased risk of postoperative infections and mortality, according to a review of studies on cardiac surgery (7-9). It is common knowledge that blood products are frequently wasted, which may indicate a lack of evidence-based procedures for blood transfusion (10-12). The writer of this paper has aimed to predict the success rate of the transfusion using the XGBoost technique and gradient boost technique.

Key Words: Blood Transfusion, Machine Learning, XGBoost, Gradient Boost, Prediction, Artificial Intelligence

1. INTRODUCTION

Before the surgery, it is necessary to provide clinicians with practical guidance for making clinical decisions and to predict RBC transfusion. On a clinical level, a patient's hemoglobin level and anemia symptoms are the primary considerations for doctors when considering a transfusion. However, other perioperative indicators, such as essential patient characteristics like sex, age, and weight, should not be overlooked; preoperative side effects like the presence of entry hypertension, ascites, and hepatic encephalopathy; and preoperative laboratory results like transaminases, creatinine, and hemoglobin. The clinical significance of intraoperative and postoperative risk factors like operation time, intraoperative blood loss, and postoperative laboratory indicators as well as the transfusion of RBCs prior to surgery are also poorly documented. Clinical prediction models and patients' preoperative risk factors have been used in studies to predict blood transfusions in craniofacial, obstetric, and joint surgery (9–11). In medicine, artificial intelligence (AI) is being used more and more to help with diagnosis, treatment, automatic classification, and rehabilitation. An AI method called the machine learning algorithm is made to mimic human intelligence by finding patterns of reasoning about the data that is available (16). Machine learning algorithms can be used to predict relevant information from basic data, like whether blood transfusions are required. Mitral valve disease patients exhibit high homogeneity, standard diagnostic and treatment procedures, comparable patient data, and a low rate of bleeding during surgery. In order to help the surgeon, determine whether or not a patient requires an intraoperative blood transfusion, we use machine learning models to investigate the risk factors that influence blood transfusion during mitral valve surgery and precisely define these factors' boundaries. Following the STROBE reporting checklist, we present the following article.

2. Literature Overview

The study aims to identify the appropriate variables and the AI method for predicting optimal demand and minimizing excess and shortage. It is intended to make predictions by taking into account the variables that will affect the prediction but have not been discussed in the literature. In the literature, variables related to human biologies like age, blood group, and gender make up the inputs of blood demand models. However, the external environment has an impact on the dynamic process of blood component demand. In contrast to other studies, the study takes into account fifteen distinct variables, including temperature, province population, and the number of operations. In the writing, no review has analyzed the outside factors that influence RBCs request. Then, based on the established variables, the AI method that best predicts demand is investigated. Weekly, unit, and average predictions from the determined AI methods were compared. The support vector machine was found to be the most suitable prediction method in light of the comparisons. A subfield of artificial intelligence that uses computational modeling to learn from data is known as machine learning. High-order relationships between covariates and outcomes can be modeled using cutting-edge machine-learning techniques even when there is a lot of data. As a result, they can be used to solve complex medical issues and typically outperform conventional statistical analysis, particularly when analyzing large amounts of medical data (12). Patients at high risk for a liver transplant receive targeted preventative measures if the RBC transfusion can be predicted prior to surgery. Patients' treatment and prognosis can benefit from reducing unnecessary costs and side effects. Traditional linear models and logistic regression (LR) are the foundations of the majority of studies on predicting RBC transfusion during liver transplantation. A machine learning model has not, however, been used to predict RBC transfusion in patients during or after liver transplantation (13, 14). This study, therefore, hypothesized that machine learning could be used to predict RBC transfusion during or after surgery using patient preoperative data. This study set out to develop a machine learning model that could predict RBC transfusion during and after surgery as well as the preoperative risk factors for RBC transfusion in liver transplant patients.

3. Methodology

3.1 Dataset

This is a classification issue based on data from the Blood Transfusion Service Center in Hsin-Chu City, Taiwan. This study utilized the donor database of the Blood Transfusion Service Center in Hsin-Chu City in Taiwan as a means of demonstrating the RFMTC marketing model, which is a modified version of RFM. Every three months, the center sends a blood transfusion service bus to one university in Hsin-Chu City to collect blood donations. We selected 748 donors from the donor database at random for the FRMTC model. Each of these 748 donor records contained the following information: R (recency), F (frequency), and M (monetary): total blood donated in c.c., T (Time - months since the first gift), and a double factor addressing whether he/she gave blood in Walk 2007 (1 represent giving blood;0 denotes non-blood donation).

	Recency (months)	Frequency (times)	Monetary (c.c. blood)	Time (months)	whether he/she donated blood in March 2007
0	2	50	12500	98	1
1	0	13	3250	28	1
2	1	16	4000	35	1
3	2	20	5000	45	1
4	1	24	6000	77	0

Figure -1: Dataset Overview

3.2 Data Preprocessing

Here in figure 2, we can see the non-null count which is very important to see if there are any data missing so that we can find it and make the dataset perfect. In figure 3 the entire description of the data is given and how it is relevant for the model to grasp the function and use any particular amount of features that can be used to increase the accuracy of the model.

```
 #   Column                                      Non-Null Count  Dtype
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 0   Recency (months)                            1000 non-null   int64
 1   Frequency (times)                           1000 non-null   int64
 2   Monetary (c.c. blood)                       1000 non-null   int64
 3   Time (months)                               1000 non-null   int64
 4   whether he/she donated blood in March 2007  1000 non-null   int64
```

Figure -2: Non-null values

	Recency (months)	Frequency (times)	Monetary (c.c. blood)	Time (months)
642	0.152778	0.102041	0.102041	0.406250
134	0.027778	0.204082	0.204082	0.895833
401	0.319444	0.081633	0.081633	0.322917
685	0.291667	0.122449	0.122449	0.375000
525	0.027778	0.061224	0.061224	0.093750

Figure -3: dataset description

3.3 Data Visualization

In figure 4 the authors are able to see that a heat map is generated on the basis of all the features that are present in the dataset and how much each feature in the dataset is relevant to the other feature and vice versa.

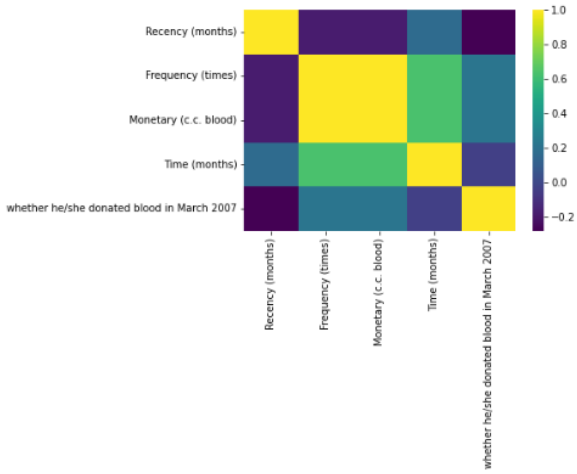

Figure -4: Heat Map

4. Model Architecture

XGBoost is a distributed gradient boosting library that has been optimized for high efficiency, adaptability, and portability. Gradient Boosting is used to put machine learning algorithms into action. XGBoost offers parallel tree boosting, also known as GBDT or GBM, which quickly and accurately solves numerous data science issues. The same code can solve problems beyond billions of examples and runs on major distributed environments like Hadoop, SGE, and MPI.

5. CONCLUSION

Finally, the authors conclude that the methods which have been used are XGBoost and gradient boost. The accuracy of XGBoost is about 93 percent and that of a gradient boost is 90 percent. A 3 percent change can be seen in the prediction hence the XGBoost performs better in this case. Hence, the prediction of the transfusion is successful with the best accuracy of 93 percent.

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