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Blood Donation Prediction using Artificial Neural Network

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Abstract: *The aim of this research is to study the performance of JustNN environment that have not been previously examined to care of this blood donation problem forecasting. An Artificial Neural Network model was built to understand if performance is considerably enhanced via JustNN tool or not. The inspiration for this study is that blood request is steadily growing day by day due to the need of transfusions of blood because of surgeries, accidents, diseases etc. Accurate forecast of the number of blood donors can help medical professionals know the future supply of blood and plan consequently to attract volunteer of blood donors to fulfill the demand. We found that the ANN model using JustNN tool led to the best test set performance accuracy of (99.31%), which is better than other studies.*

Keywords: *Blood Donation, Artificial Neural Network, JustNN, Prediction*

INTRODUCTION

The donation of blood is very important because most often people needing blood do not receive it on time causing fatality. Such people include accidents, patients suffering from malaria or organ transplants. Extreme health conditions such as Leukemia and bone marrow cancer, where affected individuals experience sudden high blood loss and need an urgent blood supply and not providing it can lead to loss of life.

One of the exciting features about blood is that it is not a characteristic product. Blood has a shelf life of approximately 42 days [7]. Whole blood is often split into platelets, red blood cells, and plasma, each having their own storage requirements and shelf life. For example, platelets must be stored around 22 degrees Celsius, while red blood cells 4 degree Celsius, and plasma at -25 degrees Celsius. Moreover, platelets can often be stored for at most 5 days, red blood cells up to 42 days, and plasma up to a one year.

Amazingly, only around 5% of the eligible donor population actually donate [11,14]. This low percentage highlights the risk humans are faced today as blood and blood products are forecasted to increase year-on-year. This is likely why so many researchers continue to try to understand the social and behavioral drivers for why people donate to begin with. The primary way to satisfy demand is to have regularly occurring donations from healthy volunteers.

In our study, we focus on building a data-driven system for tracking and predicting potential blood donors. We investigate the use of various binary classification techniques to estimate the probability that a person will donate blood in March 2007 or not based on his past donation behavior. There is a time lag between the demand of blood required by patients suffering extreme blood loss and the supply of blood from blood banks. We try to improve this supply-demand lag by building a predictive model that helps identify the potential donors.

Based on our understanding of the problem, we follow a structured analytical process widely known in the data mining community, called the Cross-Industry Standard Process for Data Mining (CRISP-DM) [6]. The idea behind this analysis framework is to develop and validate a model (or solution) that satisfies the requirements of problem and needs of stakeholders. We used guidance in the academic literature to get ideas of how others have modeled this problem and followed a similar process. Some authors clustered data before building their predictive models and some did not. We tried both and used some algorithms that others have not yet investigated to see if our solution was as good or better than what others have found.

We structured this paper as follows. We performed a review on the literature to see what methodologies have found to be successful at understanding this problem. We discuss the data set used in our study. Next, we discuss the methodology/design we implemented and discuss the models we investigated. Lastly, we present our results, discuss our conclusions, and how we plan to extend this research.

LITERATURE REVIEW

The focus of our study is to understand the performance that using traditional machine learning techniques can have at predicting future blood donation. Table 1 outlines what we believe is an exhaustive list of all published studies in this domain, the data set used, and methods employed, and results achieved. The "-" symbol indicates that nothing is reported in their paper in this table field.

Table 1: Predicting blood donation with a focus on machine learning techniques

Authors	Methods	Data	Results
[17]	ANN (MLP), ANN (PNN), LDA	Survey (430 records, 8 features)	ANN (MLP): Test accuracy (98%) ANN (PNN): Test accuracy (100%) LDA: Test

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			accuracy (83.3%)
[20]	CART	UCI ML blood transfusion data (748 donors, 5 features)	Precision/PPV (99%), Recall/Sensitivity (94%)
[7]	PCA for feature reduction ANN (MLP) vs SVM (RBF)	UCI ML blood transfusion data (748 donors, 5 features)	SVM (RBF) using PCA: Test Sensitivity (65.8%); Test Specificity (78.2%); AUC (77.5%) MLP with features recency & monetary: Test Sensitivity (68.4%); Test Specificity (70.0%); AUC (72.5%)
[19]	*J48* algorithm in Weka (aka C4.5)	Indian Red Cross Society (IRCS) Blood Bank Hospital (2387 records, features)	Recall/Sensitivity (95.2%), Precision/PPV (58.9%), Specificity (4.3%)
[14]	k-Means clustering, J48, Naïve Bayes, Naïve Bayes Tree, Bagged ensembles of (CART, NB, NBT)	Blood transfusion service center data set (748 records/donors, 5 features)	<u>Bagged (50 times) Naïve Bayes</u>: Accuracy (77.1%), Sensitivity (59.5%), Specificity (78.1%), AUC (72.2%) * model had best AUC among competing models
[29]	Fuzzy sequential pattern mining	Blood transfusion service center data set (748 records/donors, 5 features)	Precision/PPV (Frequency feature 88%, Recency feature 72%, Time feature 94%)
[22]	J48 algorithm in Weka (aka C4.5)	Blood bank of Kota, Rajasthan, India (3010 records, 7 features)	Accuracy (89.9%)
[5]	Artificial Neural Network (ANN), J48 algorithm (aka C4.5)	Survey (400 records, 5 features)	<u>ANN</u>: Accuracy (76.3%); Recall/Sensitivity (81.7%); Precision/PPV (87.9%); Specificity (53.8%) <u>J48</u>: Recall/Sensitivity (81.2%); Precision/PPV (87.3%); Specificity (52.5%)
[26]	Two-Step Clustering with CART This is fed into a serial queuing network model	Blood donation center (1095 donors, 3 clusters)	-
[1]	C5.0, CART, CHAID, QUEST	Blood transfusion center in Birjand City in North East Iran (9231 donors, 6 features)	<u>Model accuracy (train/test)</u>: C5.0 (57.49/56.4%), CART (55.9/56.4%), CHAID (55.56/55.61%), QUEST (55.34/56.11%)
[2]	Two-step clustering, C5.0, CART, CHAID, QUEST	Census survey from a blood transfusion centers from Birjand, Khordad, & Shahrivar (1392 participants)	<u>Important features</u>: Blood pressure level, blood donation status, temperature <u>Model accuracy</u>: C5.0 (99.98%), CART (99.60%), CHAID (99.30%), QUEST (89.13%)

The first published study we found investigating machine learning classification techniques to identify donors versus non-donors was by [17]. They show that it is possible to identify factors of blood donation behavior using machine learning techniques. They train and test two artificial neural network (ANN) variants; one using a multi-layer perceptron (MLP); the other a probabilistic neural network (PNN). They then compare these non-linear models to a linear discriminant analysis (LDA) model. They conclude that the ANN models both perform very well compared to LDA due the nonlinearities that exist in their data.

Authors in [20] used the Classification and Regression Tree (CART) from the University of California – Irvine Machine Learning repository. They showed on this data set that this algorithm has the ability to classify future blood donors accurately that had donated previously (i.e. recall/sensitivity of 94%). We found a very similar study published by one of the original authors the following year with a comparison of what they call a Regular Voluntary Donor (RVD) versus a DB2K7 (Donated Blood in 2007). Their key contribution was that the RVD model realized better accuracy than DB2K7. Authors in [7] extend this investigation of this data set by testing ANN with a radial basis function (RBF) as well as investigate performance using Support Vector Machines (SVMs). Even though the feature space is limited they also build and evaluate these models using principal components analysis (PCA) as feature inputs instead of the raw feature inputs. The SVM (RBF) model performed best using PCA as inputs because this model achieved the highest area under the curve (AUC) on the test set (i.e. 77.5%). The ANN model achieved the best AUC of 72.5% using only the features recency and monetary value. Lastly, we found the study design of [7] better than [20] because their models are assessed on a test (i.e. holdout) set, which provides more realistic performance on future observations. Furthermore, this design allows one to identify if a model has overfit to the data by comparing the testing set statistics to the training set statistics.

Authors in [29] investigate the use of fuzzy sequential pattern mining to try and predict future blood donating behavior. The features investigated in this study were (1) months since last donation, (2) total number of donations, (3) time (in months) since first donation, and (4) a binary feature indicating whether blood was donated in March 2007 or not. These features are similar in nature to those we investigated in our study.

Authors in [19] investigated the performance of the J48 algorithm provided in Weka3. The J48 algorithm is an implementation of the C4.5 decision tree written in Java [18,28]. They found this methodology to also perform well at predicting blood donors whom had donated before having a sensitivity of 95.2%, but performed poorly at future non-donors. They also used the J48 algorithm in Weka on a different blood donation data set obtained from a blood bank in Kota, Rajasthan, India. While they were attempting to predict the “number” of donors through their age and blood group, they actually performed a classification of donors versus non-donors which raised concerns over the validity of this study.

Authors in [5] performed a blood donation survey in Thailand. Like previous studies they used the J48 decision tree, but also tried an artificial neural network. Both models yielded similar performance with sensitivity (81.7% vs 81.2%) and specificity (53.8% vs. 52.5%)

Authors in [26] use the idea of trying to group similar donors based on arrival patterns using Two-Step clustering [24]. Then once clusters are formed, CART was implemented on the individual clusters to try to improve predictive accuracy. This approach has been tested in other domains and is an approach we investigate in our study. However, instead of Two-Step clustering we implement models based on more widely known k-Means clustering algorithm. The authors do not report the predictive accuracy of their approach, nor provide a comparison of using Two-Step clustering-CART versus using CART alone. Their primary contribution is the formulation of a serial queuing network model that could be used in the case of blood center operations where arrival patterns could be estimated and used to support workforce size utilization.

Authors in [1] collected census data collected from a blood transfusion center located in Birjand City, North East Iran. This data set consisted of 9,231 donors and measured six features. They tried to predict future blood donors using four types of decision trees (C5.0, CART, CHAID, and QUEST). Their cross-validated models all yielded poor performance ranging from 55 to 57 percent accuracy. One interesting aspect of their results was that the best performing model, the C5.0 tree, had 41 rules compared to only 13 (CHAID), 8 (CART), and 5 (QUEST). With trees the more rules (or splits) used often will lead to overfitting to the data, but can also lead to more distinct probability values in the prediction. Authors in [2] extend research into the performance of these techniques by first using two-step clustering before employing the same decision tree algorithms used in their previous study. They conclude that this approach helped them predict faster and more precisely compared to their previous study.

DATASET

The dataset used in our study is one used by others researchers studying the problem posted on the UCI Machine Learning Repository [13]. The source data has been taken from blood donor database of the Blood Transfusion Service Center in Hsin-Chu City in Taiwan. 973 donors were randomly selected from the donor database for the study. The features measured include R (Recency - months since last donation), F (Frequency - total number of donation), M (Monetary - total blood donated in c.c.), T (Time - months since first donation), and a binary variable representing whether the donor donated blood in March 2007 (1 stands for donating blood; 0 stands for not donating blood) as shown in Table 2.

Table 2: Input and output variables

Variable	Type	Input/ Output	Description
ID	Integer	Input	Donor ID
Recency	Integer	Input	This is the number of months since this donor's most
Frequency	Integer	Input	This is the total number of donations that the donor has
Monetary	Integer	Input	This is the total amount of blood that the donor has
Time	Integer	Input	This is the number of months since the donor's first
Donated blood or not	Binary	Output	This gives whether person donated blood in March 2007

METHODOLOGY

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Artificial neural networks (ANNs) are learning algorithms inspired by human brains. The main architecture of ANN is the input layer, the hidden layer and the output layer. Except for the input layer, all other layers are connected to their previous layer by weights in the form of a directed graph. The nodes represent a neuron which has a linear or non-linear activation function. The learning happens in two parts, feed-forward and back-propagation. In feed forward, weights are assigned and in back-propagation, actual learning happens. The error is calculated at each node and the weights are updated. This process is repeated until the algorithm converges. We investigated the multi-layered perceptron (MLP) neural network.

We used JusttNN tool to build an ANN model to classify whether a person donated blood in March 2007 or not. The dataset was randomly partitioned into training set and validating set using a proximately 70/30 train/validate partition.

We determined the architecture of the ANN model to contain one input layer, 2 hidden layers, and one output layer as shown in figure 1.

The dataset contains 973 samples. We divide them to 682 training samples and 291 validating samples as shown in Figure 2.

We trained the ANN Model for 80219 cycles and the validation accuracy we got 99.31% as shown in Figure 2 and Figure 4.

Finally we identified the most important input factors of the dataset that have impact on the output factor to be : Recency, Time, and Frequency as can be seen in Figure 3.

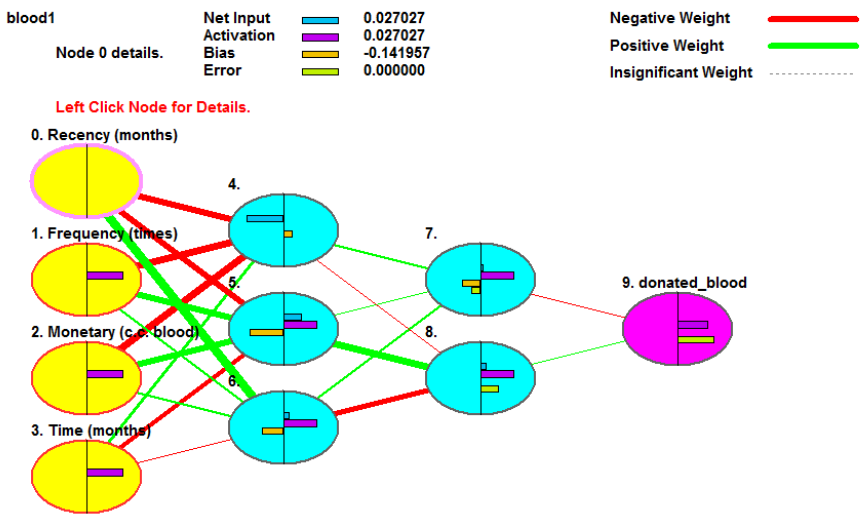


Figure 1: Architecture of the ANN model

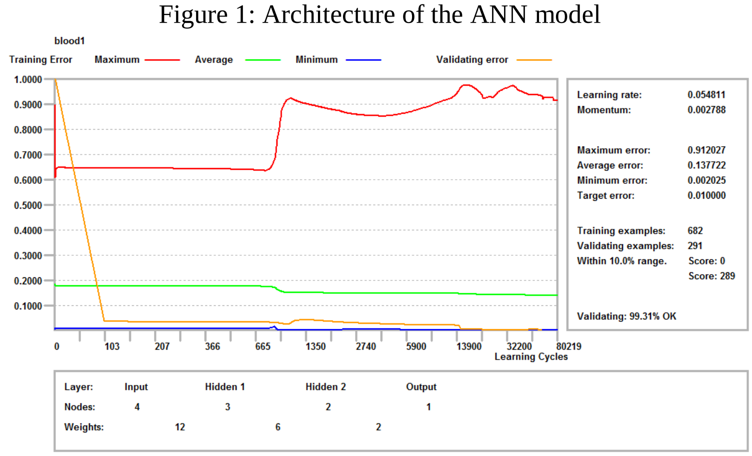
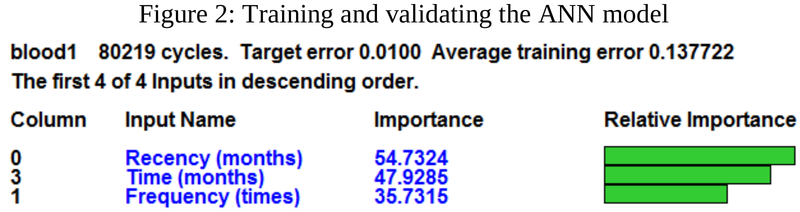


Figure 2: Training and validating the ANN model



blood1 80219 cycles. Target error 0.0100 Average training error 0.137722
The first 4 of 4 Inputs in descending order.

Column	Input Name	Importance	Relative Importance
0	Recency (months)	54.7324	
3	Time (months)	47.9285	
1	Frequency (times)	35.7315	

Figure 3: Most Important features of the ANN model

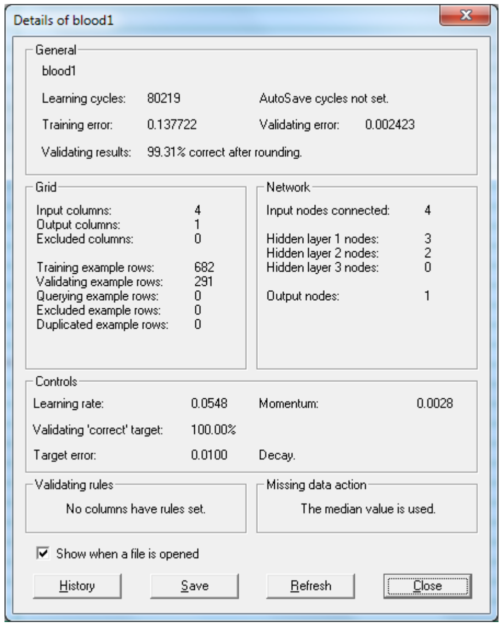


Figure 4: Details of the ANN model

CONCLUSIONS

In this study, we have proposed an ANN model for predicting whether a person is going to donate blood or not. We used JustNN tool for implementing, training, and validating the proposed ANN model. We compared the performance of our proposed model with various binary classification algorithms found in the literature using MLP, clustered data and non-clustered data to see if we can better predict if a person is going to donate blood or not.

After training and validating the ANN model, we reached an accuracy of 99.31% which is better than the previous studies outlined in the literature as shown in table 1.

Furthermore, we identified the most important input factors of the dataset that have impact on the output factor to be: Recency, Time, and Frequency.

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