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Predicting Estimated Blood Loss and Transfusions in Gynecologic Surgery Using Artificial Neural Networks

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ABSTRACT

This chapter explores valuating the efficacy of using artificial neural networks (ANNs) for predicting the estimated blood loss (EBL) and also transfusion requirements of myomectomy patients. All 146 myomectomy surgeries performed over a 6-year period from a single site are captured. Records were removed for various reasons, leaving 96 cases. Backpropagation and radial basis function ANN models were developed to predict EBL and perioperative transfusion needs along with a regression model. The single hidden layer backpropagation ANN models performed the best for both prediction problems. EBL was predicted on average within 127.33 ml of measured blood loss, and transfusions were predicted with 71.4% sensitivity and 85.4% specificity. A combined ANN ensemble model using the output of the EBL ANN as an input variable to the transfusion prediction ANN was developed and resulted in 100% sensitivity and 62.9% specificity. The preoperative identification of large EBL or transfusion need can assist caregivers in better planning for possible post-operative morbidity and mortality.

KEYWORDS

Artificial Neural Network (ANN), Backpropagation, Clinical Decision Support, Ensemble, Estimated Blood Loss (EBL), Fibroids, Gynecology, Machine Learning, Myomectomy, Surgery, Transfusion

INTRODUCTION

Uterine fibroids occur in women of reproductive age between 4.5% and 30% of the time, with over 50% of those affected claiming it negatively impacted their life (Fuldeore, & Soliman, 2017; Jayakumaran, et al., 2017; Zimmermann, et al., 2012). Myomectomy is a surgical procedure to remove fibroids that leaves the uterus intact for future pregnancies. Myomectomies may be conducted using a variety of surgical techniques including both minimally invasive techniques and standard surgical non-minimally invasive techniques. However, myomectomies are not without risk. Perioperative morbidity occurs in as high as 39% of patients (Andrade, et al., 2017; Frederick, et al., 2002; Sawin, et al., 2000) and

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although much less likely mortality still occurs (Choo, Yeo, & Thomas, 1998; Hamoda, Tait, & Edmonds, 2009; Jin, et al., 2009; Katz, et al., 2001).

Estimated blood loss (EBL) during surgery has been shown to be a statistically significant ($p < 0.05$) indicator of all perioperative morbidities using a univariate logistic regression model and also an indicator of serious perioperative morbidities using a multivariate logistic regression (Carson, et al., 2002). In addition to indicating perioperative morbidity, EBL has also been shown to be a strong indicator for other surgical outcomes including hospital length of stay (Jarnagin, et al., 2002; Sørensen, et al., 2005) and recurrence of a carcinoma (Katz, et al., 2009). The ability to preoperatively predict blood loss would allow for improved implementation of blood conservation techniques and would alert surgeons to the likelihood of related complications (Yu, et al., 2013). However, EBL is extremely difficult to measure accurately (Algadiem, et al., 2016; Eipe, & Ponniah, 2006; Guinn, et al., 2013). Prior research emphasizes the need to develop more accurate mathematical models to determine EBL (Brecher, Monk, & Goodnough, 1997).

Actual blood loss, estimated by EBL, is the most significant reason for operative and postoperative transfusions (Chang et al., 2001; Stoller, Wolf, & St. Lezin, 1994). Transfusions help to reduce mortality in patients with significant intraoperative blood loss (Wu, et al., 2010; Wu et al., 2012) and have been associated with increased postoperative morbidities (Frederick, et al., 2002). Therefore, preoperative knowledge of EBL and transfusion requirements of myomectomy patients will enable surgeons and clinicians to be better prepared to deal with probable postoperative morbidities and possible mortality.

Predictive models in medicine are most commonly developed using regression (Xie, et al., 2017). Other popular machine learning-based predictive modelling methods for clinical decision making include artificial neural networks (ANNs) and decision trees (Kourou, et al., 2015; Xie, et al., 2017). Predicting EBL is correlated with predicting transfusions and should be amenable to similar predictive informatics strategies. Prior research shows that ANNs are both a frequently used and an effective problem solving method in medicine (Cruz, & Wishart, 2006; Cunningham, Carney, & Jacob, 2000; Dreiseitl, & Ohno-Machado, 2002; Shaikhina, & Khovanova, 2017; Walczak, 2018) and for this reason ANNs are selected to try and model both EBL and transfusions.

This article examines the use of separate ANNs to predict intraoperative EBL and also perioperative transfusions and additionally introduces the novel approach in medicine of developing an ensemble ANN to predict both EBL and transfusions simultaeneously. This addresses a gap in current research where ANNs have been used to predict transfusion requirements, but primarily for cardio-circulatory surgeries (Covin et al., 2003; Walczak & Scharf, 2000). Prior research has not utilized ANNs to predict EBL or transfusions for gynecologic surgeries. A positive outcome may be able to improve surgeon and other clinician decision making regarding the intraoperative and postoperative care of these patients to help reduce morbidities and mortalities.

METHODS

Population Data

This is an IRB approved single site retrospective study. The site is a large urban nonprofit teaching hospital with an over 1000 bed count, which is the largest hospital within a 7 county region (Erickson, 2018a) and the fourth largest hospital in the state of Florida (ranked by licensed beds) (Erickson, 2018b). All records of patients receiving myomectomy surgery from October 1, 2011 to October 1, 2017 are analyzed. A total of 146 records for myomectomy were retrieved. Records were removed for cases that: did not have ultrasound or MRI confirmation (22 removed), the surgery was performed by a visiting surgeon (8 removed), the case was an incidental fibroid attached to an ectopic pregnancy (1 removed), or were cases with coexisting pathology (19 removed), leaving 96 cases. Visiting surgeon cases are removed based on prior research indicating the cadre and training of surgeons affects

Table 1. Patient demographics

Demographic Value	Mean (Standard Deviation (σ))
age (in years)	36 (4.96 σ)
BMI	28.26 (9.21 σ)
# of fibroids	3.3 (2.91 σ)
largest diameter* fibroid (in mm)	71.1 (27.75 σ)
preoperative hemoglobin	12.25 (1.46 σ)
preoperative hematocrit	37.7 (3.54 σ)
preoperative platelet count	293 (85.7 σ)
patient discharge (days after surgery)	0.58 (0.67 σ) (range 0-3)

*largest of longitudinal, anteroposterior, and transverse diameters

outcomes (Geidam, et al., 2011) and that it is difficult to compare EBL across hospitals and even surgeons, based on differing estimation methods (Brecher, Monk, & Goodnough, 1997). Coexisting pathologies are any concurrent cancer or other chronic medical condition. Table 1 displays the patient demographics for the 96 cases that were used.

The surgical techniques employed were laparoscopic, robotic, hysteroscopy, mini laparotomy, and laparotomy. The EBL across all 96 myomectomy surgeries ranged from 20 ml to 1000 ml with an average of 226.5 (165.26 σ). Seven patients (7.3%) received intraoperative transfusions of packed red blood cells, with 6 of these receiving 2 units and one receiving 3 units. This is similar to other reported findings for the rate of intraoperative non-prophylactic transfusions in myomectomy (7.5%) and amount transfused (2-3 units) (Acién & Quereda, 1996).

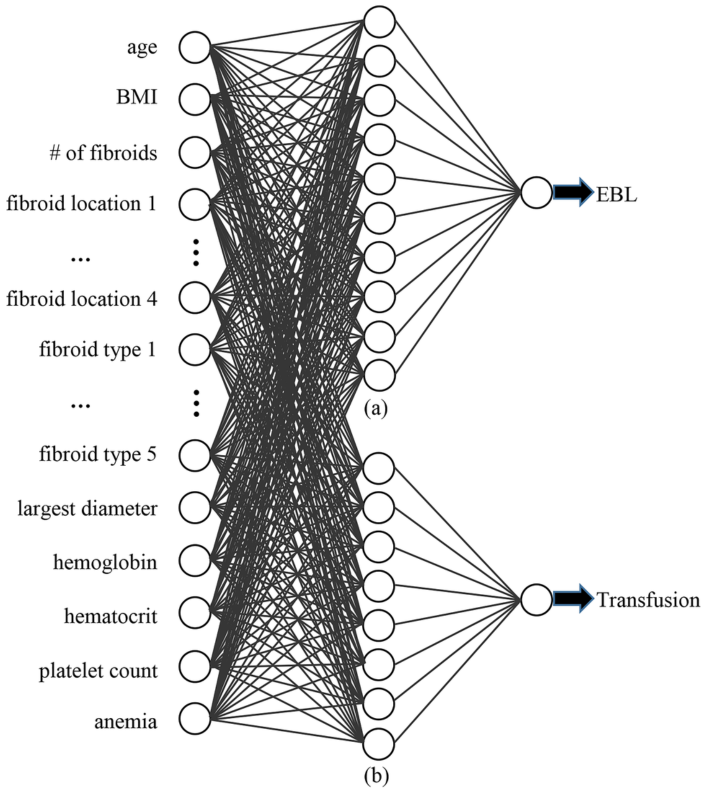
Transfusions for the current study were tracked from the time of the surgery and for up to 24 hours following surgery completion. Prior research reports combined intraoperative and postoperative myomectomy transfusions at rates from 12% to 28% (Frederick, et al., 2002; Iverson Jr, et al., 1996; LaMorte, Lalwani, & Diamond, 1993). All cases of transfusions in the current study occurred for patients undergoing a minimally invasive surgery (i.e., laparoscopic, robotic, hysteroscopy, or combination thereof).

Model Development

ANN models are developed using backpropagation (both one and two hidden layer models) and also radial basis function (RBF) learning methods. These two methods are selected due to the robustness and wide application of backpropagation networks and the ability of RBF trained networks to work well when training data is very limited and the training data may be noisy (Walczak, & Cerpa, 1999). The first ANN model developed predicts preoperatively the EBL for individual myomectomy patients and the second ANN model preoperatively predicts if transfusions will be required intraoperatively or within a 24-hour period following the end of the myomectomy surgery. A 24-hour period is used since transfusions during this time are most likely a result of the surgery and not attributable to another comorbidity.

Various architectures are attempted for each of the ANN learning algorithms and number of hidden layers, following standard research practices for ANNs (Cruz, & Wishart, 2006; Walczak, & Cerpa, 1999; Zhang, 2007). The data is divided into distinct training and validation sets and two-fold cross validation is used, with each fold having approximately half of the transfusion cases. For each ANN model, the validation data sets are presented a single time and were not used in training the corresponding ANN model.

Figure 1. Architecture of backpropagation trained ANNs to predict: (a) EBL; and (b) Transfusion requirements



The variables used in both ANN models are: age, body mass index (BMI), number of fibroids, location of fibroids, type of fibroids (i.e., submucosal, intramural, subserosal, pedunculated, unknown), largest diameter, preoperative hemoglobin, preoperative hematocrit, preoperative platelet count, and presence of anemia. All variables are numeric except for type and location of fibroids, which are categorical variables with 5 type and 4 location categories, and presence of anemia which is Boolean, resulting in an input vector of 17 variables. The EBL ANN predicts the EBL in milliliters (ml) and the transfusion ANN predicts if a transfusion will be needed intraoperatively or immediately following surgery.

The variables for the EBL and transfusion prediction ANN models are selected based on surgeon expert knowledge and prior research (as indicated below). The variables: age, number of fibroids, location of fibroids, and type of fibroids, are ubiquitous in myomectomy research (Advincula, et al., 2004; Geidam, et al., 2011). Prior research has demonstrated that BMI is correlated with EBL (Frisch, et al., 2014; George, Eisenstein, & Wegienka, 2009). Other pathology results are also commonly associated with surgical bleeding and transfusion needs including: hematocrit (Bosch, et al., 2013; Chang et al., 2001; Frisch, et al., 2014), hemoglobin (Bosch, et al., 2013; Zheng, et al., 2002), and platelet count (Bosch, et al., 2013; Cammerer, et al., 2003; Despotis, et al., 1996; Frisch, et al., 2014; Orlov, et al., 2014; Petricevic, et al., 2015). Anemia has also been shown to correlate with thrombin and platelet generation, which are related to slowing bleeding (Scharbert, et al., 2011). Anemia has been shown to be correlated with significant morbidity and mortality as well as the need for transfusions (Hare, Freedman, & Mazer, 2013).

The RBF network models follow a Moody and Darken (1989) architecture with the prototype layer starting at 50 nodes and decreased by 10 nodes for each new RBF trained model until classification performance decreases. Euclidean distance is used for the neighborhoods in the prototype layer. The first hidden layer for both the RBF and backpropagation trained ANNs starts at 10 perceptron nodes, to match the number of the different types of variables used as input, and is then increased and also decreased by 2 for successive iterations of the ANN models until validation accuracy drops by at least 5%. ANN models with a second hidden layer and trained using backpropagation are also developed with the second hidden layer starting at half the number of perceptron nodes as the first hidden layer and also increased and decreased by 2 until accuracy drops by at least 5%.

A model comparison and selection approach (Swanson, & White, 1997) is used to compare the various ANN models and select the best performing ANN model for predicting surgical EBL and similarly for predicting any transfusion requirement for myomectomy patients. Performance for the preoperative EBL prediction ANN models is evaluated by mean error in ml. Performance for the preoperative transfusion prediction ANN models is evaluated by highest sensitivity and then highest overall accuracy. The best performing learning algorithm for both prediction problems was backpropagation using a single hidden layer: 10 nodes in the EBL ANN's hidden layer and 8 nodes in the transfusion ANN's hidden layer. The ANN architectures are shown in Figure 1.

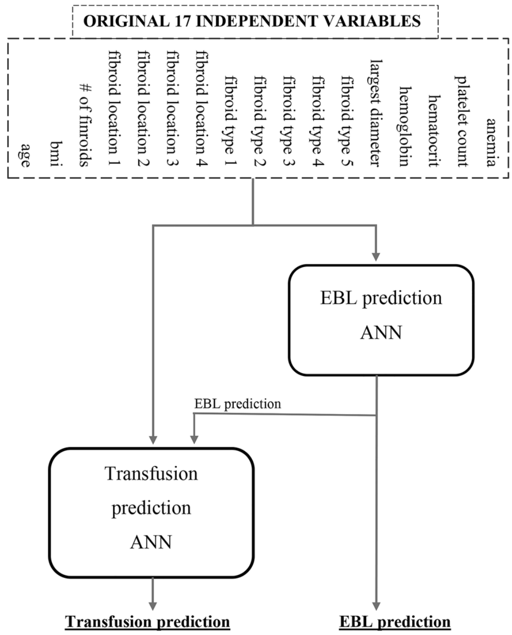
EBL is typically reported following surgeries in graduations of either 100 ml or 50 ml by most surgeons (Kiran, et al., 2004) and was true for 69 or 96% respectively of the physicians performing surgeries for the current research. Since the EBL ANN's prediction is a continuous value, the prediction is automatically rounded to the nearest 100 ml to be more meaningful to surgeons. The transfusion prediction ANN is interpreted as an indicator of the need for a transfusion of one or more units of blood product and is treated as a Boolean output of true or false.

Along with ANNs, regression models are the most popular modeling method employed for clinical decision making (Dreiseitl & Ohno-Machado, 2002; Mangiameli, West, & Rampal, 2004). Relative performance improvements afforded by ANNs are demonstrated by comparing these values to corresponding regression models that utilize the same input variables. A linear regression model is developed and used to evaluate the EBL ANN's performance. A linear regression model is chosen over a logistic regression model since the EBL is a semi-continuous value as opposed to a categorical decision and hence is more appropriate (Mood, 2010; Tu, 1996). A logistic regression model is developed and used to evaluate the transfusion prediction ANN's performance due to the discrete nature of the transfusion prediction (Mood, 2010; Tu, 1996).

Prior research has demonstrated that EBL is a primary indicator for transfusions (Chang et al., 2001; Thurer, et al., 2017). Since EBL isn't known until after the surgery, this value was not used in the initial transfusion prediction ANN, since all values are required to be available preoperatively. However, the EBL prediction ANN, shown in Figure 1, may be used for the preoperative prediction of intraoperative transfusions, if a sufficiently high EBL prediction accuracy is achieved.

Combining ANNs with other statistical, mathematical, and machine learning methods, including other ANNs, is a proven method for improving the outcome performance of ANNs (Walczak, 2012; Zhou, Wu, & Tang, 2002). The use of multiple ANNs to solve a single problem is known as an ensemble ANN. One means of combining multiple ANNs into an ensemble is to combine the output of one or more ANNs with other independent input variables to another ANN (Sharkey, 1999; Wolpert, 1992). The use of ensemble ANNs are just starting to be used in medical domains (García-Pedrajas, Hervás-Martínez, & Ortiz-Boyer, 2005), though still vastly underutilized. One form of ensemble ANN that is more widely used in healthcare are convolutional ANNs for medical image analysis (Anthimopoulos, et al., 2016; Chen et al., 2017; Tajbakhsh, et al., 2016). An ensemble approach to combine the output of the preoperative EBL prediction ANN as an input value to the transfusion prediction ANN is used to develop a new ANN ensemble to predict the transfusion need of myomectomy patients. The ensemble system is depicted in Figure 2. An ensemble ANN that combines multiple ANNs successively and utilizes output from multiple layers of the ensemble is a novel ANN modeling approach for developing predictive diagnostic and prognostic models in healthcare.

Figure 2. ANN combined ensemble model to predict EBL and transfusions



RESULTS

The prediction results for the EBL prediction ANN and corresponding regression are shown in Table 2. EBL is typically estimated by surgeons and anaesthesiologists visually during or just after surgery (Algadiem, et al., 2016; Guinn, et al., 2013) and is commonly estimated to the nearest 50 ml or 100 ml (Kiran, et al., 2004). The ANN predictions, which are continuous, are rounded to the nearest 100

Table 2. ANN prediction results for EBL (N = 96)

	ANN Predictions	Regression
Average error	127.33 ml	131.87 ml
Perfect Predictions	20 (20.8%)	20 (20.8%)
Predictions within 50 ml	36 (37.5%)	30 (31.2%)
Predictions within 100 ml	56 (58.3%)	37 (38.5%)

Table 3. Stand-alone ANN and regression transfusion predictions

	Transfusion (N = 7)	No Transfusion (N = 89)
ANN predicted transfusion	5	13
ANN predicted no transfusion	2	76
Regression predicted transfusion	4	22
Regression predicted no transfusion	3	67

ml to better simulate practice. Table 2 also contains the result of a multiple linear regression model. The regression predictions are also rounded to the nearest 100 ml to maintain compatibility with the ANN predictions. The regression model without any rounding had an average error of 131.84 ml, with zero perfect predictions of EBL and 27 predictions within 50 ml and 37 predictions within 100 ml.

The original (non-ensemble) ANN transfusion predictions are shown in Table 3 along with logistic regression model results for the same variables. The ANN demonstrates a transfusion sensitivity of 71.4% and a specificity of 85.4%, producing an overall accuracy of 84.4%. The comparable logistic regression model has a sensitivity of 57.1%, specificity of 75.3%, with an overall accuracy of 74.0%.

The prediction results for the new combination ensemble preoperative transfusion prediction ANN are shown in Table 4. The ANN demonstrates a 100% sensitivity and a 62.9% specificity, producing an overall accuracy of 65.6%. The overall accuracy and specificity of the new combined ensemble ANN are less than the original ANN model, however the sensitivity for predicting transfusion requirements is marginally significantly better than the original model that did not have any knowledge of EBL, with a p value of 0.0736 (or $p < 0.10$) calculated using a paired t-test for means with known variances.

DISCUSSION

The ANN preoperative EBL prediction model outperforms the regression model with regard to having a smaller average error, though this difference is not statistically significant. Further analysis beyond the average EBL prediction error looks at the percentage of predictions that perfectly mimic expert surgeons estimates of blood loss or are within a small discrepancy (50 or 100 ml) of surgeon estimations.

A perfect EBL prediction, shown in Table 2, means that the corresponding model's preoperative prediction exactly matches the intraoperative and postoperative EBL of the surgeon. The regression model and ANN model have identical performance in this respect. Table 2 also shows predictions that were within 50 ml and 100 ml of the surgeon's estimate, where the ANN model clearly has better performance than the regression model. These results imply that while the regression model has an identical number of perfect predictions compared to the ANN, it is making larger errors overall than the ANN model. These results for the within 50 ml and within 100 ml ANN predictions are significantly better than the regression model ($p < .001$), with Z-scores of 12.39 and 39.24 respectively. The ANN model presented here creates a method for clinicians to be aware preoperatively of the likely blood loss from myomectomy surgery and related complications, including transfusions. This will enable clinicians to be better prepared for related complications and postoperative morbidities.

The results also demonstrate that more accurate results occur when the regression model predictions (this is also true for the ANN) are rounded to the nearest 100 ml, to better simulate how clinicians estimate blood loss from surgeries. This technique may prove beneficial to future ANN and mathematical modeling research attempting to further improve preoperative predictions of EBL from various surgeries.

The EBL output is the same for both the stand-alone and ensemble ANN architectures, since the input vector and training is the same. However the ensemble ANN predictions for a probable transfusion differ, with the ensemble having 100% sensitivity versus 71.4% for the stand-alone transfusion prediction ANN, but at the sake of lower overall accuracy. The lower overall prediction

Table 4. Combined ensemble ANN transfusion predictions for myomectomy patients

	Transfusions (N = 7)	No Transfusion (N = 89)
ANN predicted transfusion	7	33
ANN predicted no transfusion	0	56

accuracy is an effect of the population distribution, since 92.7% of the studied population did not require any transfusion. Even so, the new combined ensemble ANN model is able to correctly predict almost 63% of those patients who will not require any interoperative transfusions. The original non-ensemble ANN model also outperforms the logistic regression model, with better sensitivity that is not statistically significant, but with statistically significant better specificity and overall accuracy ($p < .01$).

The new ensemble ANN requires considering additional patients as likely to need a transfusion, which in turn may negatively affect the blood order supply. The fact that for the current population the ensemble ANN identifies 100% of the patients who will require transfusions is important, even at the cost of a slightly higher false positive prediction rate. The higher sensitivity can lead to higher quality patient care through a more readily available blood product supply for patients who will require an intraoperative transfusion. The significantly higher sensitivity also improves the negative predictive value (NPV) from 97.4% for the original preoperative myomectomy transfusion prediction ANN to 100% for the new combined ensemble ANN model. The higher NPV means that if a patient is predicted to not require any transfusion, then no blood products will be needed for that specific patient's surgery.

Numerous research studies across a wide range of different types of surgeries have reported that significant blood loss and associated transfusions are highly correlated with postoperative morbidities and mortality (Carson, et al., 2002; Glance, et al., 2011; Karkouti, et al., 2004; Koch, et al., 2006). The new preoperative EBL and transfusion prediction combined ensemble ANN enables surgeons, anaesthesiologists, and follow up care team members to be more aware of possible complications and to be prepared to take proactive measures, such as changing antibiotic regimen and patient monitoring frequency. While the transfusion prediction portion of the ensemble ANN did have a lower specificity than the stand-alone ANN, which means that more patients who would not require a transfusion were identified as needing one, this does not mean that an actual transfusion would be delivered without clinical evidence to support the transfusion decision. Even though these patients were not transfused, the predicted EBL for the 40 transfusion predictions was just over 20 ml higher than the average EBL predicted for the 56 predictions that correctly indicated no transfusion requirement. This indicates that even though they were not transfused in real life, they might still have been at a higher risk for postoperative morbidities, coinciding with the need for increased attention from clinicians and possible changes in prognostic care. Combining the EBL prediction with the transfusion prediction would provide a heuristic method to further refine the ANN predictions and consequent care.

Limitations and Future Research

The current study was performed at a single site and used the surgical outcomes of patients treated by a small group of three surgeons. While the EBL and transfusion outcomes for this population were similar to several previous studies, the ability to generalize the results needs to be further evaluated to make sure that the results are not specific to the current population demographics or surgeon group. Although race and ethnicity were not considered as variables for the current ANN, the population was 45% African American, 37% Caucasian, 5% Asian, and 13% unspecified, with 16% of the total population having Hispanic ethnicity. Future research is needed to evaluate the proposed EBL ANN and both the stand alone transfusion prediction ANN and the combined ensemble ANN for transfusion prediction at other locations with differing population demographics and different surgeons to demonstrate generalizability of the results. However, because two fold cross validation is used, the results may be viewed as comprehensive for the current site and team of surgeons.

Although a number of different single hidden layer and two hidden layer architectures (number of hidden nodes per layer) were evaluated, not all possible architectures were attempted for time considerations. As such the results of the current research should be interpreted as the minimally achievable results for ANN models for preoperatively predicting EBL and transfusions for myomectomy surgeries. Additional future research could investigate additional architectures and also using other evolutionary and machine learning techniques to better estimate the architecture and desired variables. Further research should also be performed to examine other possible input variables and different combinations of the current input variable set, which may further improve the ANN prediction result by eliminating noise from unnecessary variables (Walczak, & Cerpa, 1999). While the current ANN results are compared against regression models, future research could also compare the results of the ANN and ANN ensemble models against another commonly used machine learning approach in medicine: decision trees and random forests.

Finally, the current research predicts if any transfusion will occur. Future research, using previously unused ensemble ANNs for transfusion prediction could examine predictions of the actual quantity of transfusions to occur, which for the current research was 0-3 units of packed red blood cells. The ensemble ANN methodology serves as a model for improving transfusion predictions and may work well for predicting the actual number of units for other surgeries that have a wider range of administered transfusions.

Clinical Application

While the research presented demonstrated a new ensemble ANN architecture for predicting EBL, this study shows a proof of concept, demonstrating the efficacy of ensemble ANNs for predicting EBL and transfusions to guide preparation for surgery and indicate to clinical teams possible surgery related complications. Clinical implementation of the ANN as a clinical decision support (CDS) tool is achievable.

The patient demographics of age and BMI should already be available from the patient's electronic medical record (EMR). Additionally, since scans of the tumors are done prior to surgery these notes will also be available in the EMR. Blood pathology is typically ordered from days to just before surgery. Utilization of the described ANN ensemble would require blood pathology to be completed sufficiently far in advance of surgery to enable ordering of appropriate blood supplies. Modern medical systems will automatically load test results into a patient's EMR. Kuperman et al. (2007) state that intelligent CDS systems are becoming ever more embedded within EMRs. Other research has reviewed the positive clinical outcomes associated with electronic CDS systems (Pawloski, et al., 2019). Therefore, it is possible to implement the ensemble ANN as an electronic CDS embedded within EMR systems, to automatically have access to the required preoperative variables, to predict EBL and transfusions. Alternatively, the ensemble ANN could easily be implemented as a stand-alone electronic CDS that would have values entered from an EMR. Future applied research is needed to develop the clinical implementation and evaluate the effectiveness in managing blood order supply and improving patient outcomes.

CONCLUSION

The presented research demonstrates the efficacy of ANN models for predicting surgical blood loss and transfusion requirements for myomectomy surgery patients. A combined ensemble style ANN is developed that utilizes the output of the EBL prediction ANN as an input value to improve the sensitivity of transfusion predictions. Utilizing the predictive output of ANNs from multiple layers within the combined ensemble ANN is a new architecture that should be considered for clinical diagnostic and prognostic prediction models of correlated outcomes. Ensemble ANNs have been significantly underutilized in medical research. The improved sensitivity indicates that ensemble ANNs should be considered as a modeling alternative in cases where increased sensitivity is desired, with a possible tradeoff in reduced specificity.

Evaluating EBL has always been a difficult problem for surgeons and anaesthesiologists and is prone to error (Algadiem, et al., 2016; Eipe, & Ponniah, 2006; Guinn, et al., 2013). The EBL prediction ANN provides a machine learning based method to preoperatively predict surgical blood loss with reasonable accuracy, perfectly predicting almost 21% of the studied surgical cases and predicting an additional 37.5% within 100 ml of actual EBL. This enables prognostic prediction ANNs to utilize previously unavailable information such as surgical blood loss, utilizing the designed ensemble architecture.

The reported research has two primary contributions and a secondary contribution (2.a):

1. The efficacy of utilizing ensemble ANN architectures for medical diagnostic and prognostic systems has been demonstrated and specifically shown to improve the sensitivity for transfusions predictions over non-ensemble ANN architectures;
2. An ANN approach for preoperatively predicting EBL has been developed. When used in an ensemble ANN. This permits the introduction of previously unavailable variables for preoperative prediction of outcomes:
    a. The demonstrated capability of ANNs to predict EBL and transfusions may be used to help identify patients who are at increased risk of post-surgical morbidities and mortality.

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