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Application of Artificial Neural Networks to Predict Prolonged Operative Timing during Laparoscopic Colorectal Cancer Surgery

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ABSTRACT

Aim: Prolonged operative timing is likely to negatively impact clinical outcomes and accurate preoperative prediction of those likely to undergo longer procedures can assist theatre planning and postoperative care. We aimed to apply artificial neural networks (ANN) as a predictive tool for prolonged operating time in laparoscopic colorectal surgery.

Methods: A dedicated, prospectively populated database of elective laparoscopic colorectal cancer surgery with curative intent was utilised. Primary endpoint was the prediction of operative time. Variables included in the network were: age, gender, ASA, BMI, stage, location of cancer, and neoadjuvant therapy. A multi-layered perceptron ANN (MLPNN) model was trained and tested alongside unit and multivariate analyses.

Results: Data from 554 patients were included. 400 (72.2%) were used for ANN training and 154 (27.8%) to test predictive accuracy. 59.3% male, mean age 70 years, and BMI of 26. 161 (29%) were ASA III. 261 (47%) had rectal cancer and 8.5% underwent neoadjuvant treatment. Mean operative time was 218 minutes (95% CI 210-226) with 436 (78.7%) of less than 5 hours and 16% conversion rate. ANN accurately identified and predicted operative timing overall 87%, and those having surgery less than 5 hours with an accuracy of 93.3%; AUC 0.843 and 93.3%. The ANN findings were accurately cross-validated with a logistic regression model.

Conclusion: Artificial neural network using patient demographic and tumour data successfully predicted the timing of surgery and the likelihood of prolonged laparoscopic procedures. This finding could assist the personalisation of peri-operative care to enhance the efficiency of theatre utilisation.

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Introduction

Since the introduction of minimally invasive surgery (MIS) in 1991, the laparoscopic technique has rapidly evolved across all specialities with an increasing uptake of robotic technologies [1-4]. The benefits of the minimally invasive approach have been well documented in terms of postoperative pain, shorter hospital stay, improved cosmesis and quicker return to normal function [5-12]. However, these must be weighed against the limitations, which include a long learning curve and increased operative time particularly with advances in training/techniques allowing surgeons to operate on more complex cases [11-15]. Prolonged operative timing is likely to negatively impact clinical outcomes following laparoscopic colorectal resection [16]. A metanalysis looking at the impact of prolonged operative time across various specialties showed statistically significant data of increased complications with time increments [17]. Prolonged surgery has an additional impact on health care economics [18].

Optimising cost-effectiveness of health care is a modern challenge for the NHS. Trusts in England estimate a £2.3 billion deficit by the end of 2016 [18]. Additionally, the COVID-19 pandemic has created unprecedented challenges including great backlog of waiting lists for routine operations, estimated at 5.7 million [19,20]. Therefore, it is essential that every effort is made to make each service as efficient and as cost-effective as possible, without compromising patient care. Thus, an accurate prediction of operative timing is essential in operative room planning. Additionally, knowledge of factors that can accurately predict prolonged surgery is important for theatre planning, aiming to enhance perioperative efficiency and accurately plan theatre resources [21,22].

The application of Artificial Neural Networks (ANN) has been widely adopted across various medical specialties. Within in-surgery there are promising results for applying ANN including diagnosis and predicting cancer outcomes including survival [23-25].

This study aimed to apply artificial neural networks (ANN) as a predictive tool for operating time and identify those who are likely to have prolonged laparoscopic colorectal cancer surgery.

Methods
An observational review of a dedicated, previously reported colorectal cancer patient database was performed [26]. Inclusion criteria were patients with biopsy proven colorectal adenocarcinoma undergoing elective laparoscopic surgery with curative intent, data were collected over 12 years. Exclusion criteria included metastatic disease, those who underwent open surgery or were unfit for resection. Patient and tumour demographics were captured. Total operative time was defined as the time taken from entering to the anaesthetic room to leaving the theatre to recovery to completion of skin closure. Other operative factors such as total blood loss and conversion from laparoscopic to open surgery were recorded. Conversion from laparoscopic to open surgery was defined as the inability to complete the dissection laparoscopically, including vascular ligation, and usually, but not always, requiring an incision larger than that required to remove the specimen.

Artificial Neural Network (ANN)
ANN is a computational model composed of many highly interconnected processing elements (neurons) working in unison. Neural networks process information in a similar way with the human brain and like people, ANNS learn by example. Detailed ANN descriptions have previously been provided [26-28].

Statistical Analysis
The data was analysed using SPSS (v24; SPSS Inc, Chicago, IL, USA). For categorical data, analysis included the use of cross tabulation, odds ratios & chi-square to test the difference or association between groups.

Multivariate association between variables was assessed using **binary logistic regression**. Only those variables identified as being significantly associated with diagnosis to treatment in the univariate analyses were included in the modelling process. The data was screened for potentially influential observations, and the extent of multicollinearity amongst predictor variables was examined using variance inflation factors. The sample size is perceived to be sufficiently large to ensure stable logistic regression parameter estimates were obtained which are not suspected on accuracy or precision. Odds ratio for individual variables is computed from the regression equation as OR = eB adjusted for all other variables simultaneously. The effect magnitude was quantified using the odds ratio (OR) with 95% confidence interval.

Multilayer Perceptron Neural Network (MLPNN) application in SPSS was used in this analysis. This involved having neurons with an input layer (*independent variables*), one hidden layer, and an output layer (*outcome*: *Dichotomised Operative* Time: *OT => 5 hours & 0= < hours*). The layers are interconnected and learns by example through adjusting the "weight" of each link between the neurons as shown in Figure 1, which allows adaptation of the model and accurate prediction [29,30].

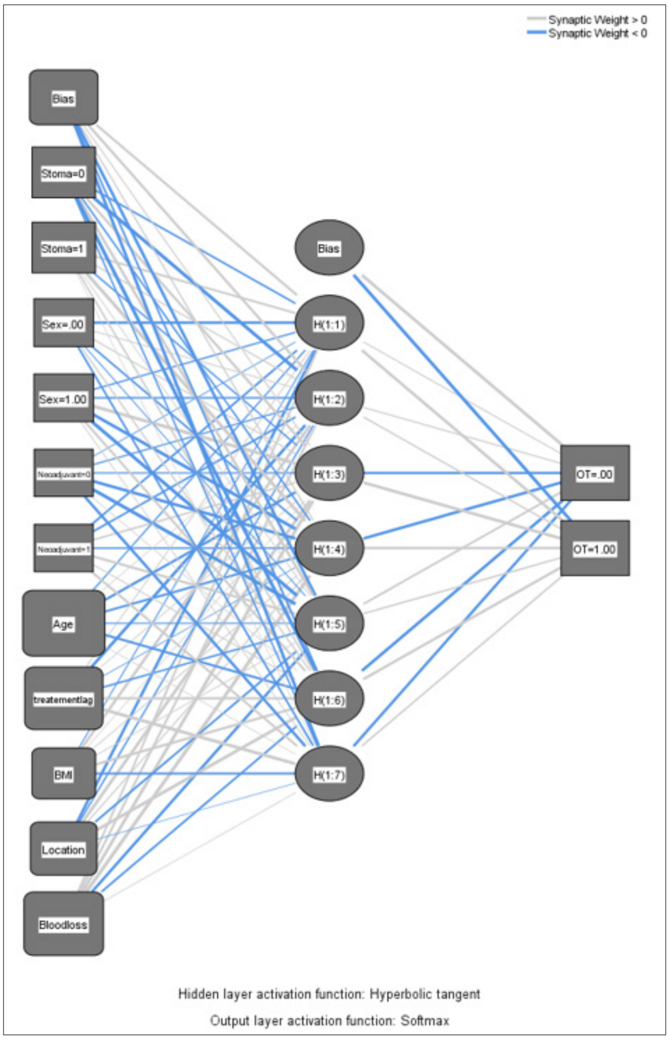

Figure 1: Schematic of multilayer perceptron neural network for prolonged operative timing

Artificial Neural Network Cross Validity
Receiver operator characteristics curves (ROC), area under the curve (AUC), gain and lift charts, and comparison with logistic regression modelling were used for cross-validation of the ANN. The predictive quality of our ANN was tested using the patients in the data set that had not been used in the training phase.

Results
590 patients were selected, 554 were included, and 36 excluded due to incomplete data. Four hundred patients' data sets (72.2%) were used for ANN training and 154 (27.8%) to test predictive accuracy. 59.3% male, mean age 70 years, and BMI of 26. 161 (29%) were ASA III. 261 (47%) had rectal cancer and 8.5% underwent neoadjuvant treatment. Mean operative time was 218 minutes (95% CI 210-226) with 436 (78.7%) of less than 5 hours and a conversion rate of 16%.

The neural links are shown in Figure 1. Four hundred (72.2%) were selected as training cases with 154 (27.8%) used to test the predictive function of the ANN. Variables included in the MLPNN network were: age, gender, ASA, BMI, stage, location of cancer, neoadjuvant therapy, time from diagnosis, and planned stoma. Our ANN model identified; Neoadjuvant therapy, age, and BMI as the best independent predictors of prolonged operative timing (Table 1).

Table 1: Importance of Artificial Neural Network Predictive Variables

Independent Variable Importance		
	Importance	Normalized Importance
Sex	.058	24.4%
ASA	.042	17.8%
BMI	.158	66.2%
Tumour Location	.095	40.1%
Stage	.035	14.8%
Neoadjuvant Therapy	.032	13.5%
Stoma	.131	55.1%
Treatment Lag	.238	100.0%
Age	.210	88.1%

Validation of MLPNN

1. Classification: As Table 2 shows, our MLPNN correctly classified 111/119 (93.3%) cases that were under 5 hours operating time and predicted 23/35 (65.7%) cases accurately that were equal to or over 5 hours of operating. Overall, correctly predicted operative time in 87% of testing cases. The significant predictive properties of the MLPNN were confirmed by creating an ROC curve for both predictions of prolonged operative timing with an area under the curve of 0.893 for both < and > 5 hours (Figure 2).
2. Gains Chart: A gain chart was also created demonstrating if we use half of the sample (50% population using the diagonal line) and guess as to who is likely to have operative timing over 5 hours then are likely to get 50% true positive guesses. If we use the ANN model, we only need to have 30% of the sample to give us over 80% of true positive predictions compared to 50% by random selection by 50% of the population (Figure 3).
3. Lift Chart: The lift chart (Figure 4) illustrates that if we use the ANN and select only 10% of our sample (blue), we would be greater than 3.5 times more likely (red) to get a true positive prediction compared to using random selection
4. Artificial Neural Network Cross Validity and development of Prediction Score

Table 2: Application of Artificial Neural Network to Predict Operative Timings

Sample	Observed	Predicted		
		< 5 hours	>= 5 hours	Percent Correct
Training	< 5 hours	289	28	91.2%
	>= 5 hours	28	55	66.3%
	Overall Percent	79.3%	20.8%	86.0%
Testing	< 5 hours	111	8	93.3%
	>= 5 hours	12	23	65.7%
	Overall Percent	79.9%	20.1%	87.0%

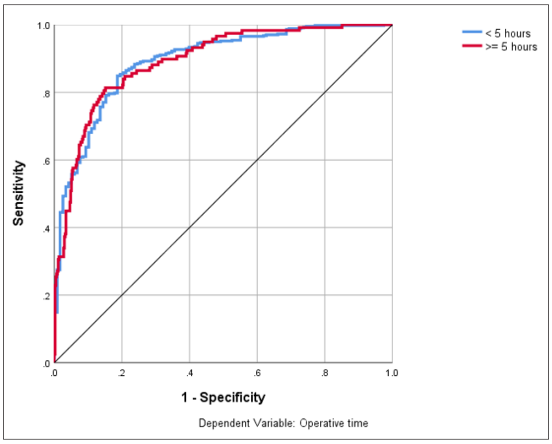

Figure 2: Receiver operator characteristic curve for predictive properties of the MLPNN for prolonged operative timing

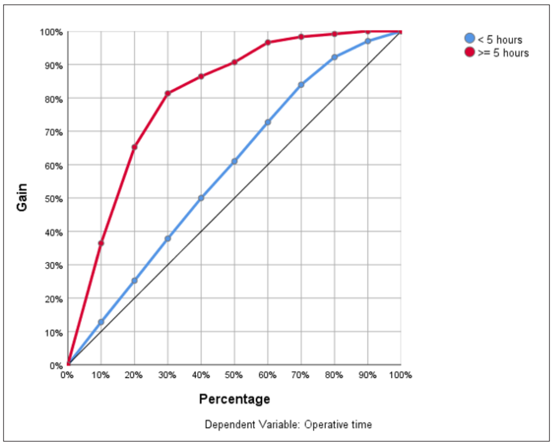

Figure 3: Gain chart for predictive properties of MLPNN for prolonged operative timing

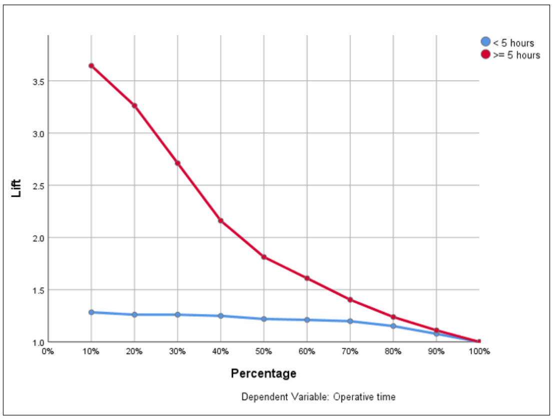

Figure 4: Lift chart for predictive properties of MLPNN for prolonged operative timing

Logistic regression model to cross-validate the ANN results. This demonstrated the same factors to predict prolonged surgical timing including neoadjuvant therapy, age, sex, BMI, tumour location, and stoma formation (Table 3). A prediction score was then calculated from all predicting variables in the multivariate analysis (logistic regression) and the linear function of the binary logistic regression model: Predictive score = B1x1 + b2x2.....+ Constant

Predictive score based on this data:
positive score OT > 5 hours = -.043xAge + .605xSex (1 male /0 female) +.056xBMI + .919x Tumour Location (1 Rectum

/0 Colon) + 1.825x (Stoma 1 yes 0 No) + .001x Blood loss in mls + .006x Time Lag – 2.345. The model has demonstrated good predictive properties with an area under the ROC amount to 0.843 (Figure 5).

Table 3: Logistic Regression Model

Variable	B	Significance	Exp(B)	95% CI for OR EXP(B)	
				Lower	Upper
Age	-.043	.000	.958	.935	.981
Sex	.605	.037	1.831	1.037	3.233
BMI	.057	.045	1.059	1.001	1.119
T. Location	.919	.007	2.507	1.293	4.862
Stoma	1.825	.000	6.205	3.164	12.169
Treatment lag	.006	.001	1.006	1.002	1.010
Constant	-2.345-	.047	.096		

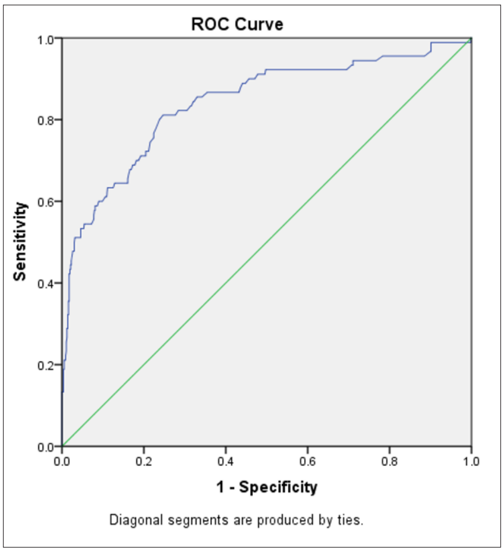

Figure 5: Receiver operator characteristic curve for predictive properties of the logistic regression model for prolonged operative time. Area under the curve 0.843

Discussion

Predicting operative timing is challenging, involving multiple variables but essential for preoperative planning. Non-linear interaction between the different elements affecting operative timing makes it difficult to assess which variable will have the greatest impact on operative time. In this study, using artificial neural networks, we have predicted prolonged operative time within laparoscopic colorectal cancer and generated a prediction score that can be used in future research and service development.

Accurately predicting operative time is key to streamlining theatre management including time slots, correct staffing levels and reduced cancellations, managing expectations, and improving patient care and experience. The application of MLPNN was consistent with conventional logistical regression analysis in identifying the same factors that can predict prolonged surgery. It is interesting to note that the strongest predictor of prolonged operative timing was neoadjuvant therapy, then age and then BMI.

Most of the identified predictive factors for prolonged surgery are clinically justified, as neoadjuvant therapy and male sex are generally associated with difficult rectal cancer surgery. It was interesting, however, to see that age among those factors. This could be explained by the fact that elder patients require more anaesthetic preparation, which is included within the operative time.

Operating theatres are one of the most expensive areas in a hospital to run, with an average cost of approximately £1200/hour [31]. They also represent one of the most profitable areas of healthcare delivery for NHS trusts, if delivered efficiently. Streamlining could lead to significant savings. For example, the NHS Institute for Innovation and Improvement calculated that the average trust has an opportunity to save £7 million a year in efficiency savings by running a 'productive theatre' [32]. Although longer operations are sometimes inevitable, knowledge of this beforehand can limit the increased cost associated with a prolonged operation. For example, the estimated operative duration is used to arrange operating room schedules and allocate staff [32]. If a case extends longer than expected, this could increase costs, as improper scheduling can lead to overtime pay, perioperative inefficiency, and personnel misallocation [21,22,33]. Overtime pay is costly, erosive to morale, contributing to burn out and lack of theatre staff retention. In our cost-minded healthcare system, predicting operative time is crucial for cost-effectiveness.

Limitations

The definition of prolonged operative timing is arbitrary (5 hours) based on a previous study indicating that procedures taking longer than 5 hours were associated with a significant increase in length of stay and blood loss [16].

Although widely used by technology and analytical companies, ANN presents some considerations when applied to healthcare scenarios. Even for common clinical situations, the size of datasets is unlikely to match those analysed by the industry, therefore, may not be able to accommodate a large number of input variables or achieve the highest level of accuracy. To a degree, this could be offset by performing state-wide registry-based ANN testing, subject to data protection and confidentiality considerations. This could inform benchmarking and quality assurance processes as well as informing public health and healthcare policy. Central limit theorem could also be expected to balance out many factors that can influence patient care. Matched institutional specific ANN could help inform planning for individual patients as this network would incorporate local provider factors that are likely to influence time to surgery. Our findings now require larger scale study and validation in external centres.

Conclusion

Artificial neural network using patient demographic and tumour data successfully predicted the timing of surgery and the likelihood of prolonged laparoscopic procedures. This finding could assist the personalisation of peri-operative care to enhance the efficiency of theatre utilisation.

Conflict of Interest: The authors declare that they have no conflict of interest

Ethical consideration: For this retrospective study already held, anonymised patient data, formal ethical approval for this type of study was not required. The patient database was originally created with local research ethics and data governance committee approval.

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