Optimising Intra-operative Pressure Injury Prevention in Surgery: Investigation of Machine Learning Classification Framework

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INTRODUCTION

Hospital acquired pressure injuries (HAPIs) are associated with known risk factors including decreased mobility, surgical duration, vasopressor infusion, excessive moisture, and altered perfusion. HAPIs are still mostly unexamined in the critical care population [1] with very few risk assessments taken intra-operatively; patients who undergo surgery and older than 65 years are higher risk compared to younger patients acquiring PIs [2,3]. Peri-operatively, skin assessment is performed pre/post-operatively. With high-risk surgeries ranging up to 6+ hours, patients' skin is left unobserved. Subsequently post-operative PIs occur. Pressure relieving devices have been developed for other hospital settings such as the use of redistribution and low air mattresses or manual repositioning [4]. However, during surgeries such as spinal surgeries this is impossible. In most cases the use of these redistribution devices is impossible to integrate intra-operatively as they could distract, cause injury to the patient and disrupt the clinician's workflow. The prevalence of PIs in surgical patients undergoing spinal surgery in prone position was 23% [5], thus supporting further investigation into intra-operative monitoring or assessment during surgery. This research investigates the use of intra-operative sensors to identify patients at risk of developing an Intra-operatively Acquired Pressure Injury (IAPI).

This research aims to leverage intra-operative pressure sensor data and demographic data from a participatory study. We identified relevant variables and explored their contribution to machine learning model performance training set in predicting the response of a visual high against three different test methods.

MATERIALS & METHODS

A study was conducted to determine location of bone location and high-pressure areas on a spinal surgical frame. Participants were prone for 5 minutes and documented their perceived comfort levels using a visual analog scale and demographic information. Data from suspected bone/ high pressure areas were collected by sensor matrices. The sensor matrices comprised of four, 8x8 custom flat matrices designed to be integrated to the specific frame and are connected to a microcontroller. Analog signals were processed into data visualisation; visualisation represented as jpeg files, these were visually assessed and noted whether they contained a visual high peak. The training set was put into The MathWorks Inc (2023) *Statistics and Machine Learning Toolbox [R2023a].* 3 test methods were compared; demographic data; sensor data; combined (sensor and demographic).

RESULTS

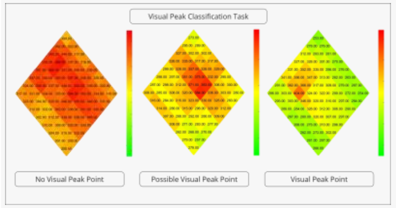

Figure 1. Classification task identifiers, no visual peak (0), possible peak (1) and visual peak (2)

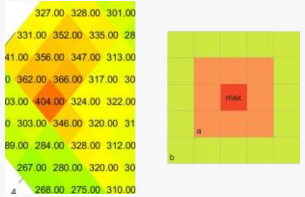

Figure 2. Visual high Peak point example and the max, a, and b relationship.

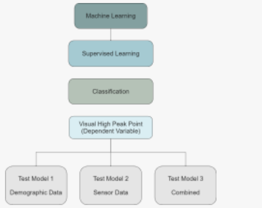

Figure 3. Flow diagram of study protocol used and the 3 different test structure.

The visual assessment were categorised as a visual peak classification task (figure 1), and split into 3 classification classes, 'No visual peak point' (0), 'possible visual peak point' (1), and 'Visual peak point' (2) (figure 2). Confusion matrices were created for each test model (figure 4) and the accuracy, precision, recall and F1 score calculated. From the results, the demographic model is the least accurate, 66.7% and the sensor model is the most accurate, 87.5%. Both the sensor model and the combined model fair well with precision and have true positives for both 'No Visual Peak' and 'Visual Peak Point' making no errors in distinguishing between the two classes. Features were highlighted below in table 2, in the combined model the features considered important were BMI, 'a', 'b' and range.

Table 1. Ranking Machine Learning Models and Confusion matrix

Test model	Model	Accuracy	Precision	Recall	F1- Score
1. Demographic data	Medium Neural Network	0.667	0.78	0.67	0.65
2. Sensor Data	Medium Neural Network	0.875	0.92	0.91	0.876
3. Combined Data	Efficient Linear SVM	0.79	0.86	0.8	0.79

Table 2. Multiple Feature Ranking Algorithm and highest feature importance

	MRMR	Chi2	ReliefF	ANOVA	Kruskal Wallis
Demographic Data	BMI	BMI	BMI	BMI	BMI
	Survey	Weight	Age range	Weight	Weight
	Age range	Height	Survey	Age Range	Age Range
Sensor Data	a	a	b	b	b
	Max reading (sensor)	Standard deviation	Range (sensor)	Range (Sensor)	Range (sensor)
	b	Variance	a	a	a
Combined. (Demographic and Sensor Data)	a	b	b	b	b
	Max reading (sensor)	Standard deviation	BMI	Range (sensor)	Range (sensor)
	BMI	a	Age range	a	a

Figure 4 – Confusion matrices; model 1 (demographic), model 2 (sensor), model 3(Combined)

CONCLUSIONS

In this study it was determined that the combination of sensor data and demographic data creates a reasonable accuracy of 0.79. The model presented for the combined model, Linear Support Vector Machine (SVM), exhibited good precision (0.86) and does not mistake the difference between 2 very striking classes. The main sensor features of this model were 'a' (the nearest grouping of neighbours from the max), 'b' (the next groupings of neighbours surrounding 'a') (figure 2) and range. Features 'a' and 'b' are percentage changes from the maximum sensor peak point, they detail the distance of radiating sensor value change and play a crucial role in the feature ranking algorithms. The demographic data that was crucial as a main feature is Body Mass Index (BMI), BMI has a U-shaped relationship with PIs [6], meaning those who are malnourished or underweight BMI <18.5 and those who are obese >30 are more at risk of developing PIs. The BMI, high peak point (max), a and b correlation needs to be explored further to be able to identify to what extent these features are weighted. These results contain promising finding that have proven a preliminary machine learning model that could be used in providing live data feedback to the clinicians on IAPI during surgery.

LIMITATIONS

This study demonstrated the inclusion of sensor data alongside demographic data from a participatory study. However, the study only contained 24 participants and this type of dataset is limiting to machine learning. To further build on the results, a larger number of participants will be needed, with greater focus on interactions of the highest value point in the matrix and the radial value change from the max, 'a' and 'b'. Further studies are necessary to evaluate the feasibility of applying this in a clinical setting and inclusion of more observations and features (predictors).

LITERATURE CITED

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CONFLICTS OF INTEREST

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FURTHER INFORMATION

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