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Precision depth of anaesthesia estimation through machine learning and regression method: an intriguing case study unveiling the future

Mohammad Reza Gharib, Najmeh Jamali, Atefeh Roustaei, Najme Mohammadyahya

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Precision depth of anaesthesia estimation through machine learning and regression method: an intriguing case study unveiling the future

Mohammad Reza Gharib

Department of Mechanical Engineering,
University of Torbat Heydarieh,
Torbat Heydarieh, Iran
Email: m.gharib@torbath.ac.ir

Najmeh Jamali* and Atefeh Roustaei

Department of Industrial Engineering,
University of Torbat Heydarieh,
Torbat Heydarieh, Iran
Email: najmejamali7@gmail.com
Email: Atefeh.Roustaei@gmail.com
*Corresponding author

Najme Mohammadyahya

Electrical Engineering Department,
University of Houston,
Texas, USA
Email: nmohamm8@cougarnet.uh.edu

Abstract: We introduce a novel propofol dosage prediction method for anaesthesia induction, emphasising the role of regression. Diverging from conventional reliance on mathematical models, our approach harnesses machine learning and data mining techniques for heightened accuracy. Experiences from past drug dosage errors inform the development of software that autonomously refines predictions. By extracting crucial information from datasets, machine learning techniques predict anaesthesia levels. This study focuses on applying regression techniques to anaesthesia research, mitigating the severe consequences of drug dosage errors. Our method demonstrates high precision, emphasising age and gender as crucial factors in predicting drug dosage. This contributes significantly to anaesthesia depth estimation, enhancing patient safety and reducing costs in Iranian surgical operating rooms. Integrating machine learning into drug dosage prediction shows potential for precision and efficiency in anaesthesia induction. However, thorough validation, considering medical history and concurrent medications, is essential before clinical implementation to ensure safe and effective anaesthesia.

Keywords: regression method; machine learning; optimisation; depth of anaesthesia; artificial intelligence.

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Biographical notes: Mohammad Reza Gharib is an Associate Professor at the Department of Mechanical and Industrial Engineering University of Torbat Heydarieh, Iran. He received his PhD in the field of Mechanical Engineering from Ferdowsi University of Mashhad. His areas of interest include the modelling of systems such as MEMS/NEMS, control systems, optimisation in healthcare systems, and robotics.

Najmeh Jamali received her PhD in Industrial Engineering from the Yazd University, Yazd, Iran. Her research interests include optimisation in healthcare systems, artificial intelligence application in medicine, mathematical modelling. She joined the Department of Mechanical and Industrial Engineering at the Torbat Heydarieh in 2016 as a Visiting Professor Lecturer. <http://orcid.org/0009-0008-6990-2092>.

Atefeh Roustaei is a graduate of Industrial Engineering from Torbat Heydariyeh University, and her field of activity and research is in the fields of optimisation of general industrial engineering topics.

Najme Mohammadyahya is a PhD student in Electrical Engineering at the University of Houston, Texas, USA, whose field of work is improvement and optimisation of warning sensors in the field of healthcare.

1 Introduction

Analgesia, hypnosis, and relaxation of muscles are the three primary factors that are addressed during the anaesthetic procedure in order to produce the ideal patient condition during surgical intervention. The anaesthesiologist manually modifies the dosage of medicines according to the patient’s vital signs and their expertise in the traditional method (Pasin et al., 2017). Because of this, the entire process is dependent on the human, who is susceptible to stress, inability to pay attention continuously, and tiredness (particularly during prolonged interventions), all of which can result in non-optimal medication dose (Merigo et al., 2019; Ionescu et al., 2014). As a result, this could end up in postoperative problems brought on by inadequate or excessive medicine doses. Automated control for medication infusion systems can help anaesthesiologists with this challenging work by addressing some of these problems (Jamali et al., 2020).

Researchers have been interested in the control systems design for the depth of anaesthesia primarily because of its difficult and complicated nonlinear nature (Merigo et al., 2019; van Heusden et al., 2019). Due to its predictive nature and limitations management method, model predictive control has also received significant attention (Lai et al., 2020; Hatib et al., 2018). Several publications, including Jamali et al. (2021a, 2022) have examined the use of MPC approaches to manage the level of anaesthesia when propofol is used. The potential for anticipating a patient’s reaction to medication delivery is the primary cause of this interest (Nogueira et al., 2021). The strategies discussed in Kadakia et al. (2019), Jin et al. (2021) and Irwin et al. (2020) concentrate on

inter-/intra-patient variability, aiming to reduce the model uncertainties that are the most susceptible component of MPC approaches. These methods typically provide complicated control systems with high computing demands that are difficult to re-tune or modify (Pawłowski et al., 2023). They are also intriguing from a clinical standpoint because they can be used to create customised controls for each patient by utilising a parameterised patient model based on unique physiological characteristics like gender, weight, height, and age to enhance the prediction capability (Ionescu et al., 2014; Khodaei et al., 2020; Joosten et al., 2019). The goal of prediction is to help improve the condition of patients, and many studies and research have been done on data mining techniques and methods (Naşcu and Pistikopoulos, 2017). The data mining process involves a large volume of data and is a combination of machine learning (ML), statistical science, and database. Given the large volume of data in the medical field, this process plays a significant role in disease management, diagnosis, and treatment (Nimmo et al., 2019; Moayedi et al., 2020).

Most of the recent developments in control systems are negatively affected by process noise, resulting in suboptimal control resource utilisation (Schiavo, 2023; Pawłowski et al., 2023; Jamali et al., 2023). While a noise filter in the feedback loop can help mitigate this problem, it requires a trade-off between noise attenuation and process dynamics modification (Gharib, 2020; Koochi et al., 2022). This issue is especially critical in the depth of anaesthesia control tasks and is exacerbated when using predictive control approaches. An alternative to traditional time-based control schemes is an event-based control system, which can reduce noise impact on control action variability and improve resource utilisation by triggering the controller task based on controlled variable dynamics rather than time progress (Pawłowski et al., 2016). The event-based control approach is an effective technique that has been proposed for bioprocesses and energy systems, where optimal control resource usage is critical, but it may result in some sacrifice of control performance. However, this approach is promising for depth of anaesthesia control during surgeries, and some studies have already investigated its use with a proportional-integral-derivative (PID) controller and its modification (Merigo et al., 2018; Merigo et al., 2020).

ML is usually evaluated through the pre-processing phase. Pre-processing helps to transform raw data into a suitable form for the next learning stage (Murphy, 2012). The pre-processing stage involves data extraction, cleaning, transformation, and integration to make it usable for learning. The evaluation results can lead to adjusting the learning algorithm's parameters or selecting another algorithm (Pawłowski et al., 2022; Ntouskas and Sarimveis, 2021). ML algorithms are classified into three categories, supervised learning, unsupervised learning, and reinforcement learning. The most well-known algorithms are decision trees (DT) and random forests. The term data mining refers to the semi-automatic process of analysing large datasets to find useful algorithms. In solving many problems in ML many input features are not all suitable for solving the problems. Feature selection is one of the important stages in creating a suitable training model (Ribba et al., 2022; Rani and Pravin, 2021). The ML approach, inspired by pattern recognition and computational learning theory, studies and develops algorithms that can learn from data and make predictions. These methods are used in programming explicit algorithms that have suitable performance and address user needs. The process of ML involves feeding data into an algorithm, which then uses statistical methods and mathematical models to analyse the data and identify patterns. The algorithm is then

trained on this data, adjusting its parameters until it can accurately predict outcomes for new data (Jamali et al., 2020, 2021b; Pesapane et al., 2018).

The paper proposes a regression model that uses machine learning (ML) to estimate a patient’s depth of anaesthesia during surgery, to improve patient safety, and avoid fatal errors by detecting errors in drug dosage levels. The main contribution of the work is to explore the potential of using ML techniques, specifically regression, for predicting the depth of anaesthesia. The proposed model emphasises the significance of data mining and artificial intelligence in predicting data, and how these techniques can be applied to achieve the goal of estimating the depth of anaesthesia.

2 The depth of anaesthesia estimation model

2.1 Patients’ data

In this article, a dataset has been used to estimate the depth of anaesthesia in patients. The dataset includes features such as gender, age, height, weight, blood pressure, heart rate, actual propofol dose, estimated dose, induction stages, and patient’s depth of anaesthesia. These features were collected in a clinical setting during the patients’ surgeries and included 32 patients, 18 of whom were male and 14 were female.

Demographic information, such as gender, age, weight, and height, was obtained from medical reports. In addition, information about diagnosis, treatment method, total length of the procedure, and initial propofol dose was also collected.

Table 1 The average demographic information of patients

<i>Demographic information</i>	<i>Average numbers</i>
Age	37.46
Gender	18 M, 14 F
Weight (kg)	65.31
Height (cm)	166.68

2.2 Machine learning with regression model

In this study, we aimed to estimate the depth of anaesthesia in patients using a dataset that included various features such as gender, age, height, weight, blood pressure, heart rate, actual propofol dose, estimated dose, induction stages, and patient’s depth of anaesthesia. The data was collected in a clinical setting during the patients’ surgeries. The statistical population of the study was 32 patients, and the researchers used field research methods to collect the data. They first examined the accuracy of the numbers in the dataset and then calculated the estimated depth of anaesthesia using the regression method. The main goal of the study was to provide a practical application of ML to estimate the depth of anaesthesia and control the process during surgeries. The results of the study could potentially improve patient safety by detecting errors in drug dosage levels and ensuring the correct depth of anaesthesia is achieved during surgeries.

Machine learning (ML) with regression models involves using models to predict continuous variables based on one or more continuous independent variables. This technique involves defining a regression model to predict the value of a continuous

variable based on the values of one or more independent variables, using optimised machine learning algorithms. Two types of regression models can be applied, equations (1) and (3), which are linear and Lasso regression. The regression model with gradient descent is a machine learning algorithm that trains a regression model by iteratively adjusting the coefficients to minimise the error between the predicted values and the actual values. The algorithm updates the coefficients iteratively until the cost function converges to a minimum, as formulated in equation (2) for the linear regression model with gradient descent. The Lasso regression model is also used to reduce overfitting in regression models, as described in equation (4).

2.2.1 Linear regression model

$$\{y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon\} \quad (1)$$

where y is the dependent variable, $x_1, x_2, \dots, x_n$ are the independent variables, $\beta_0, \beta_1, \dots, \beta_n$ are coefficients, and ε is the error term.

2.2.2 Linear regression model with gradient descent

$$\beta_j = \beta_j - \alpha \times \frac{\partial J(\beta)}{\partial \beta_j} \quad (2)$$

where β_j is the linear regression model's j^{th} coefficient, α is the learning rate, $J(\beta)$ is the cost function, which measures the error between the predicted values and the actual values, and $\frac{\partial J(\beta)}{\partial \beta_j}$ is the partial derivative of the cost function with respect to β_j .

2.2.3 Lasso regression model

$$\{y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \varepsilon - \lambda \sum |\beta_i|\} \quad (3)$$

where y is the variable that is dependent $x_1, x_2, \dots, x_n$ represent the independent variables. The error term for the model is represented by ε , and λ is the regularisation parameter. Also, $\beta_0, \beta_1, \dots, \beta_n$ are coefficients.

2.2.4 Lasso regression model with coordinate descent

The Lasso regression model with coordinate descent is a machine learning algorithm that trains a Lasso regression model. It works by iteratively adjusting the coefficients to minimise the sum of the squared errors and the L_1 penalty term.

$$\beta_j = \frac{\text{soft_threshold}(z_j, \lambda)}{(x_j^T x_j)} \quad (4)$$

The formula in equation (4) is used to find the β_j coefficients. β_j is the j^{th} coefficient of the Lasso regression model, z_j is the j^{th} coordinate of the residual vector, λ is the regularisation parameter that controls the strength of the L_1 penalty term, and x_j is the j^{th} column of the design matrix. The algorithm updates the coefficients until convergence,

using a coordinate-wise descent approach to handle the L_1 penalty term, as described in equation (5).

$$\text{soft_threshold}(z, \lambda) = \text{sign}(z) \times \max(|z| - \lambda, 0) \quad (5)$$

2.3 The learning rate and the regularisation parameter

In machine learning, two important hyperparameters are the learning rate and regularisation parameters. The learning rate determines how much the model's coefficients are updated at each iteration during training, controlling the step size in the gradient descent algorithm used to minimise the cost function. A higher learning rate can lead to faster convergence but also increases the risk of overshooting the optimal solution or getting stuck in a local minimum, while a lower learning rate can be more stable but slower to converge, as shown in equation (2).

The regularisation parameter controls the trade-off between fitting the training data well and avoiding overfitting, which is when the model becomes too complex and fits the noise in the training data, leading to poor generalisation and high variance. Regularisation techniques such as L_1 and L_2 regularisation add a penalty term proportional to the absolute value or square of the coefficients, respectively, to the cost function. The regularisation parameter, λ , determines the strength of the penalty term and how much the model is encouraged to avoid overfitting. A higher λ can help prevent overfitting but also reduce the model's ability to fit the training data well, while a lower λ increases the risk of overfitting but allows the model more freedom to fit the training data well, as shown in equations (6), (7) and (8).

$$\text{minimise } J(\beta) + \lambda \times R(\beta) \quad (6)$$

where $J(\beta)$ is the cost function, $R(\beta)$ is the regularisation term, and λ is the regularisation parameter.

2.3.1 L_1 regularisation

$$R(\beta) = |\beta_1| + |\beta_2| + \dots + |\beta_n| \quad (7)$$

For L_2 regularisation, the regularisation term is the square of the coefficients:

$$R(\beta) = \beta_1^2 + \beta_2^2 + \dots + \beta_n^2 \quad (8)$$

The regularisation parameter λ is responsible for controlling the penalty term's strength, which in turn affects the model's tendency to overfit. Higher values of λ result in stronger regularisation and more heavily penalised models, while lower values of λ lead to weaker regularisation and models that are freer to fit the training data well.

Note: It is important to note that both the learning rate and the regularisation parameter play crucial roles in ML, but their relative importance varies depending on the problem and data characteristics. The learning rate is more important for controlling the optimisation process's speed and stability during training, while the regularisation parameter is more important for controlling the bias-variance trade-off and preventing overfitting. In practical ML applications, it's often necessary to tune both the learning

rate and the regularisation parameter to achieve optimal performance on the validation data. This paper applies this process to achieve the best results.

3 Results and discussion

Regression analysis is a statistical tool that is commonly used in many fields, including economics, social sciences, engineering, and medicine. It is used to estimate the strength and direction of the relationship between two or more variables. The findings of this study are compared with the findings of the field research. The similarity between the findings of this study and the field research indicates that this type of system is capable of accurately modelling propofol dosage. Table 2 shows the induction stages, estimated dose, actual dose, and percentage error for each stage.

Table 2 The regression estimation model of the propofol dose

<i>Induction stage</i>	<i>Estimated dose</i>	<i>Actual dose</i>	<i>Percentage error</i>
1	1.6	1.498	0.102
2	1.6	1.497	0.103
3	1.6	1.496	0.104
4	1.6	1.495	0.105
5	1.6	1.495	0.105
6	1.6	1.475	0.125
7	1.6	1.474	0.126

Table 2 shows the estimated dose, actual dose, and percentage error for each induction stage. The estimated dose is the dose of propofol estimated by the regression model, while the actual dose is the dose administered during the induction stage. The percentage error is the difference between the estimated and actual doses, expressed as a percentage of the actual dose. The percentage error for each stage is relatively low, ranging from 0.102% to 0.126%. This suggests that the regression model used in this study is capable of accurately estimating the propofol dose during the induction stages. However, it is important to note that these results are based on a small sample size of 32 patients and may not be representative of the wider population. Further research on a larger sample size is needed to confirm the accuracy of the regression model. Table 3 shows the induction stages, the actual depth of anaesthesia, the ideal depth of anaesthesia, the percentage error, and the propofol dose estimated by the regression model.

Table 3 shows the actual depth of anaesthesia, the ideal depth of anaesthesia, the percentage error, and the propofol dose estimated by the regression model for each induction stage. The ideal depth of anaesthesia is the target depth of anaesthesia for each stage, while the actual depth of anaesthesia is the depth measured during the induction stage. The percentage error is the difference between the actual and ideal depths of anaesthesia, expressed as a percentage of the ideal depth. The propofol dose estimated by the regression model is the dose required to achieve the estimated depth of anaesthesia.

Table 3 indicates that the actual depth of anaesthesia for each stage deviates from the ideal depth, with percentage errors ranging from -9.50% to 41.51%. The regression model estimates the propofol dose required to achieve the estimated depth of anaesthesia,

which ranges from 1.474 to 1.498. The results suggest that the regression model can accurately estimate the propofol dose required to achieve the desired depth of anaesthesia. However, the actual depth of anaesthesia achieved during the induction stages deviates from the ideal depth, indicating that additional factors beyond the propofol dose may be influencing the depth of anaesthesia. Therefore, further research is needed to identify and account for these factors to improve the accuracy of anaesthesia depth estimation.

Table 3 The regression estimation model of anaesthesia depth

Induction stage	Actual depth	Optimal depth	Percentage error	Propofol dose
1	91.51	50	41.51	1.498
2	82.56	50	32.56	1.497
3	73.60	50	23.60	1.496
4	64.65	50	14.65	1.495
5	55.70	50	5.70	1.495
6	50.46	50	0.46	1.475
7	41.50	50	-9.50	1.474

Table 4 shows the estimated propofol doses, propofol doses used in the regression model, actual propofol doses, and the difference between the estimated doses and the doses used in the regression model.

Table 4 The comparison between the regression model and real data

Estimated dose (mg)	Dose in regression (mg)	Actual dose (mg)	Error (mg)
346.5	363.985	364.0	17.485

Figure 1 The inputs and output of the proposed regression model (see online version for colours)

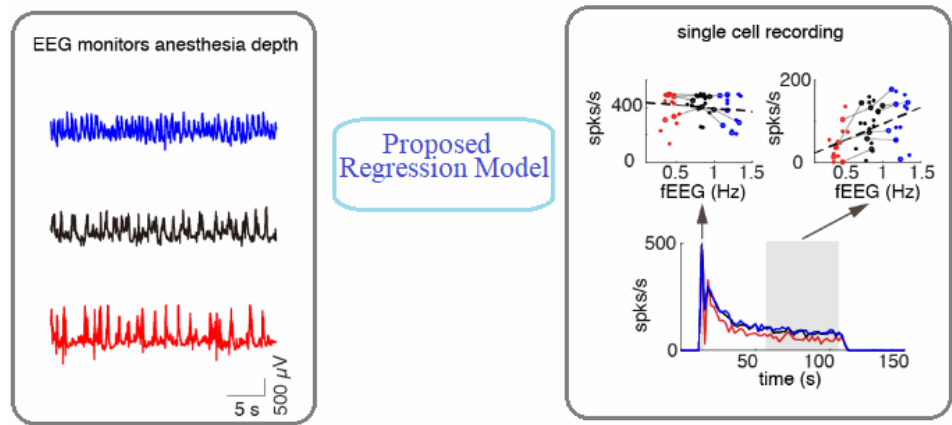


Table 4 indicates that the estimated propofol dose is 346.5 mg, while the propofol dose used in the regression model is 363.985 mg. The actual propofol dose administered was 364.0 mg. The difference between the estimated dose and the dose used in the regression model is -17.485 mg. These results suggest that the regression model used in this study

may slightly overestimate the propofol dose required for anaesthesia induction. The difference between the estimated dose and the dose used in the regression model may be due to differences in individual patient responses to anaesthesia or variations in the anaesthesia induction process. Further research is needed to determine the causes of these differences and to improve the accuracy of propofol dose estimation.

Figure 2 The comparison of anaesthesia depth estimates with regression and field methods (see online version for colours)

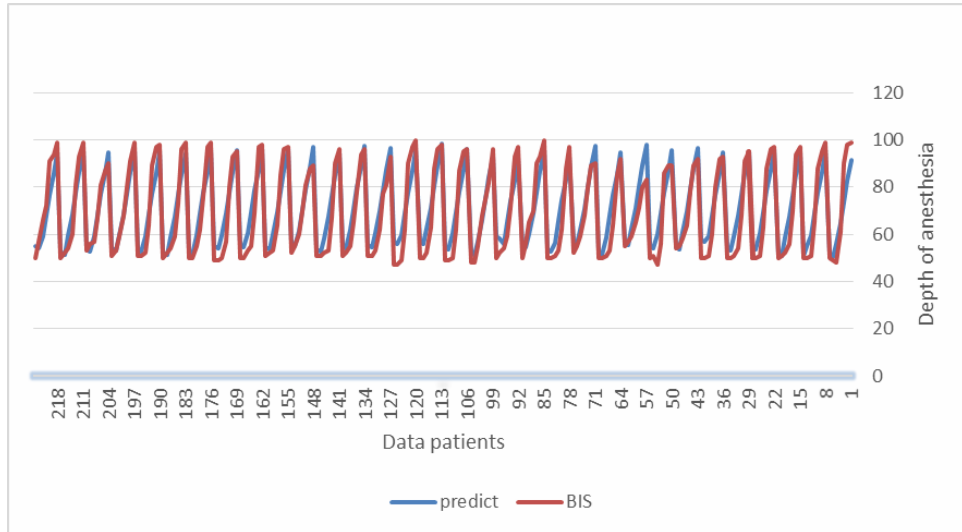
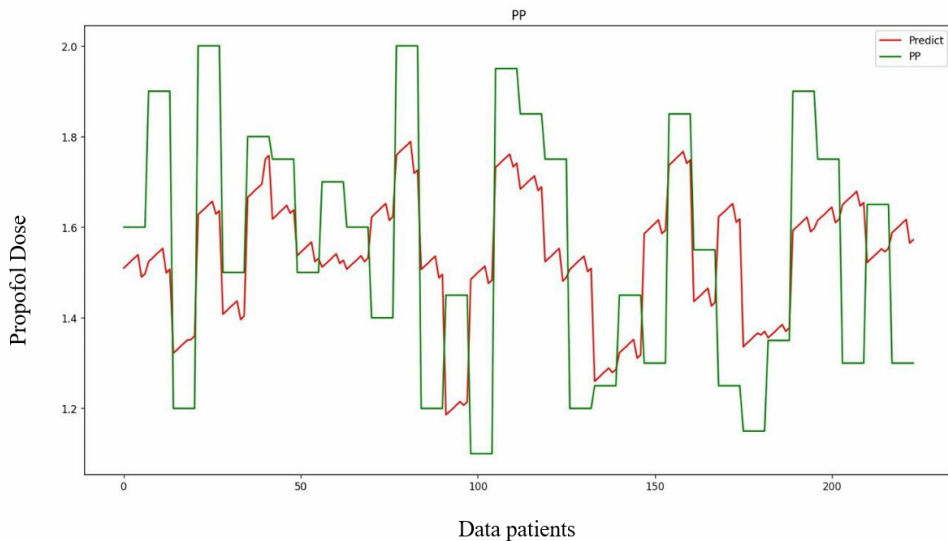


Figure 3 The comparison of propofol dose estimates with regression and field methods (see online version for colours)



The data division process can be divided into two stages of training and testing. Initially, the data is divided into three parts: training data, validation data, and test data. Generally, the number of training data is higher than the number of validation and test data. Since the number of input and output data is equal (224), and in each category, the number of input and output data is the same.

Table 5 Data information

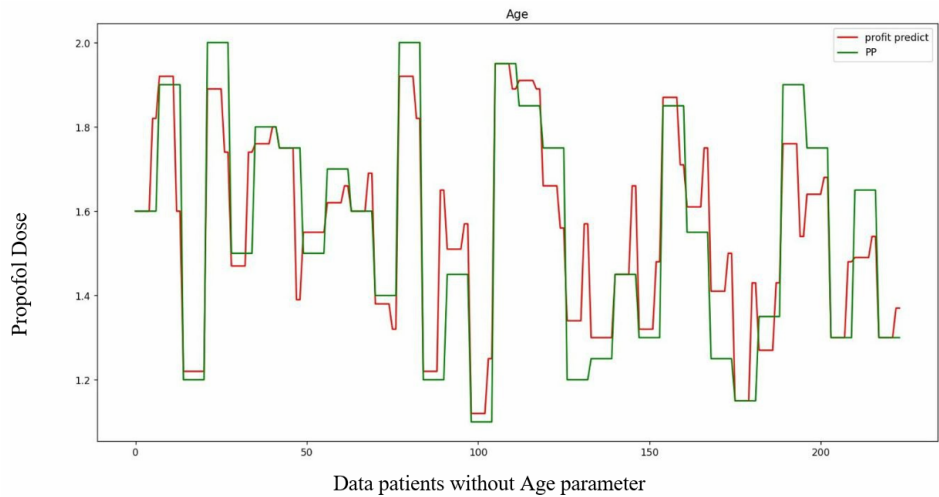
	<i>Training data</i>	<i>Validation data</i>	<i>Test data</i>
Input	134	56	34
Output	134	35	55
Total	224	90	89

In general, this method of dividing data into two stages of training and testing is regular and common in machine learning. In this method, training data is used to train the model, validation data is used to adjust the model parameters, and test data is used to evaluate the performance of the model. Using this method, the model can be improved, and overfitting or underfitting can be prevented.

Table 6 Time running of model

	<i>Millisecond</i>
The execution time of the program for 32 data	68.76
the execution time for the 33rd data	20.75

Figure 4 The propofol dose estimation without age (see online version for colours)



The difference in execution time between these two cases may be due to various factors, such as the characteristics of the 33rd data, the algorithm used in the program, the complexity of the program, or the processing power of the computer running the program. It is important to note that the execution time of a program may vary depending on the size and complexity of the input data, as well as the hardware and software configuration of the computer running the program. Therefore, it is important to test the

program with different input data and on different machines to get a more accurate estimate of its execution time.

Figure 5 The propofol dose estimation without weight (see online version for colours)

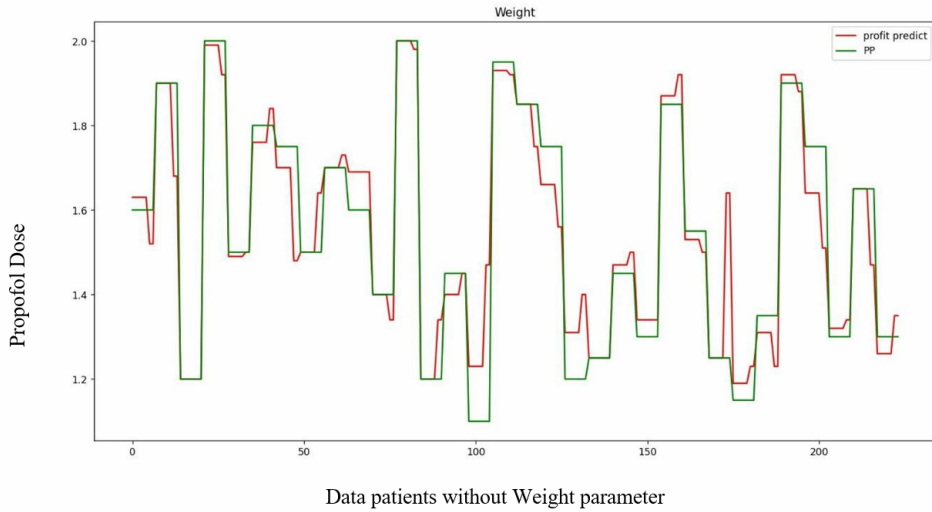
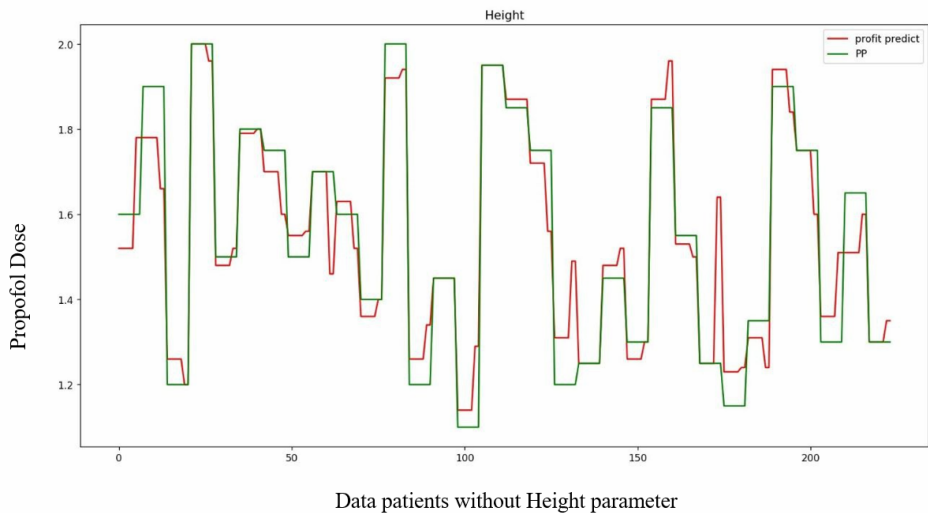


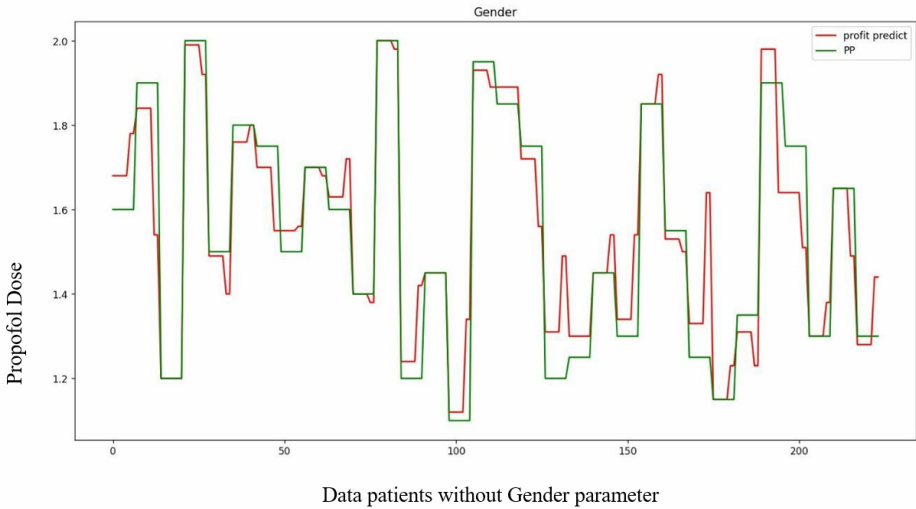
Figure 6 The propofol dose estimation without height (see online version for colours)



Based on Figures 4 to 7, propofol dosage is heavily influenced by weight and age, with weight having a greater impact on drug prescription. This is because propofol is a highly lipophilic drug that distributes rapidly into adipose tissue and has a high volume of distribution in obese patients. Therefore, it is important to consider the patient's weight and age when prescribing propofol to achieve the desired level of anaesthesia and avoid adverse effects. The effects of weight and age on propofol dosage should be carefully

considered by anaesthesiologists and healthcare professionals to ensure the safe and effective administration of the drug.

Figure 7 The propofol dose estimation without gender (see online version for colours)



Propofol is a commonly used intravenous medication for sedation and anaesthesia induction in medical procedures. The dose of propofol required for anaesthesia induction varies depending on various factors such as age, weight, sex, and medical history of the patient. However, weight and age are considered to be the most important factors that influence propofol dosage.

In general, obese patients require higher doses of propofol due to their larger volume of distribution. On the other hand, elderly patients may require lower doses of propofol due to age-related changes in metabolism and pharmacokinetics. Therefore, it is essential to consider the patient's weight and age when calculating the appropriate propofol dose. The use of standardised dosing guidelines based on weight and age can help to reduce the risk of over- or under-dosing and ensure safe and effective anaesthesia induction. In addition to weight and age, other factors such as patient medical history, comorbidities, and concurrent medications can also influence propofol dosage. Therefore, it is important for healthcare professionals to carefully evaluate each patient's individual characteristics and medical history before administering propofol to ensure safe and effective anaesthesia induction. Table 7 shows the accuracy of different parameters in predicting propofol dosage:

Table 7 The sensitivity analysis of patient's physiological parameters from propofol dose estimation

Parameter	Accuracy (%)
Age	93.28
Weight	90.66
Height	82.394
Gender	95.840

Table 7 indicates that age and gender are the most accurate parameters in predicting propofol dosage, with accuracy rates of 93.28% and 95.840%, respectively. Weight is also a relatively accurate parameter, with an accuracy rate of 90.66%. However, height is a less accurate parameter, with an accuracy rate of 82.394%. It is important to note that the accuracy of these parameters may vary depending on the specific patient population and the predictive model used. Therefore, it is essential to validate the accuracy of the predictive model and the selected parameters for each patient population before using them in clinical practice. Additionally, other factors such as medical history, comorbidities, and concurrent medications should also be considered in predicting propofol dosage to ensure safe and effective anaesthesia induction.

4 Conclusions

In conclusion, data mining is an effective technique for extracting valuable insights and knowledge from large and intricate healthcare datasets. It has the potential to improve patient outcomes, improve healthcare delivery, and inform healthcare sector decision-making processes. The precision of data mining results and the validity of the employed models are crucial factors that must be considered to ensure the dependability and utility of the resulting insights. This study demonstrates that data mining can be used to predict patient outcomes and treatment as well as to minimise absolute error in a homogenous patient population. The findings also demonstrate the importance of factors in age, weight, and gender when estimating propofol dosage or anaesthesia depth.

There are ethical and privacy concerns associated with the use of patient data, despite the fact that data mining has tremendous potential in the healthcare industry. Healthcare organisations and professionals must ensure that patient data is collected and used ethically and responsibly and that measures are in place that maintains patient confidentiality and privacy. Future research should concentrate on developing more accurate and effective predictive models, investigating new applications of data mining in healthcare, and addressing the ethical and privacy concerns associated with the use of patient data. Overall, data mining in healthcare has the potential to revolutionise our approach to patient care and treatment.

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