APPLIED RESEARCH

Machine Learning Predicts Patient Tangible Outcomes After Dental Implant Surgery

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ABSTRACT Dental implants have become increasingly important in daily dental offices. The degree of pain and discomfort experienced during a surgical procedure varies from one patient to another. Using advanced machine learning algorithms to predict pain, the dentist and the patient would make more informed decisions about the treatment. This study aims at Predicting postoperative discomfort using an AI-based multi-linear regression model. The functional parametric association between the eight parameters (age, sex, and operating technique) and the patient's postoperative pain was established following implant surgery. The output was normalized information regarding both incidence and severity of immediate discomfort post-implant surgery. To enhance the generalization ability of the multiple linear regression (MLR) model and avoid overfitting, 825 cases were provided as the training set, while 207 cases were given for data authentication. In addition, 45 samples were used as controls to determine the model's prediction accuracy. Evaluation of the given model reveals a Root Mean Squared Error of 0.1085. This prototype predicted AI model postoperative pain following implant surgery with 89.6 % accuracy. Finally, this AI model exhibited clinical viability and utility in predicting postoperative pain after surgery.

INDEX TERMS Artificial intelligence, technology, multi-linear regression model, pain, swelling.

I. INTRODUCTION

Dental procedures have always been a source of anxiety and apprehension for most patients [35]. Dental anxiety, apprehension, and dental pain are inexorably linked to avoidance of dental care. Generally, drilling, injection (anesthesia), and extraction can provoke anxiety in patients. This ostensibly leads many to defer necessary dental treatment due to their anxiety and aversion to dental procedures [2].

The emergence of dental implants has revolutionized dentistry. Restoring lost teeth with dental implants has become

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a widely accepted primary treatment option [14]. Dental implants have a high success rate and a low incidence of morbidity. However, implant placement is inexorably linked to postoperative pain, an inconvenient consequence of tissue damage during implant placement [32], [33].

Pain is a complex and often chronic phenomenon that remains imperfectly understood [27]. Higher anxiety can lower the pain threshold.(Vedolin, Lobato, Conti, & Lauris, 2009) Uncontrolled pain invariably affects patient experience and can have severe medical and legal ramifications [26], (Schropp, Isidor, Kostopoulos, & Wenzel, 2004) Postoperative pain and its diagnosis depend on the patient's subjective feelings and the patient's perspective. Self-reporting

of pain is highly subjective, can be influenced by myriad factors [17], and may not be an optimal marker for pain management [8]. Factors not limited to the procedure, such as age, gender, anxiety level, and history of habits, can worsen pain perception [13]. Chronic pain may be associated with interrupted work and emotional distress, compromising the lifestyle of an otherwise healthy individual [7].

Methods for controlling or reducing postsurgical pain and discomfort are non-steroidal anti-inflammatories (NSAIDs), acetaminophen, opioids, and corticosteroids [30]. Postoperative swelling or edema correlates to the extent of surgical trauma, number of implants, heat generation during placement, and duration of surgery [3].

The clinical skill and expertise of the operator help reduce peri-operative and postoperative pain [13]. Efforts must be made to limit the pain and encourage healing and osseointegration. A clear understanding and effective pain management can engender trust between the doctor and the patient and improve treatment outcomes.(Náfrádi, Kostova, Nakamoto, & Schulz, 2018).

Artificial intelligence (AI) refers to the use of algorithms to enable machines to learn by studying datasets to recognize and solve problems through decision-making [34]. Artificial intelligence is already part of our lives, from social media to traffic analysis and industrial applications [34]. Most applications of AI in healthcare are still in the research and development stage [10], [16], [24], [25]. In dentistry, AI may assist human researchers and clinicians, relieving them of routine laborious tasks and providing sustained high throughput performance [28], [29]. In anesthesiology, AI is being examined in pain Management [5] (Tighe et al., 2012), anesthesia monitoring(Ortolani et al., 2002; Shalbaf, Saffar, Sleigh, & Shalbaf, 2017), control(Olesen et al., 2018), and ultrasound guidance(Pesteie, Lessoway, Abolmaesumi, & Rohling, 2017).

AI can detect patterns in subgroups of highly dimensional datasets to uncover patterns enabling the forecasting of future data, effectively learning from the troves of patient information obtained. This knowledge can be applied to develop pain prediction models to forecast clinical pain ratings accurately.(Soyiri & Reidpath, 2013) Applying comprehensive and universal preventative pain management can be problematic due to adverse side effects associated with analgesic interventions. Predictive pain models can help establish targeted pre-emptive analgesia for postsurgical pain patients at risk of chronic pain. An ideal pain prediction model could serve as a reliable indicator and predict pain in a diverse population with widely varying implant outcomes. This would reduce the burden of postoperative pain and could reduce healthcare costs.(Vadivelu et al., 2014)

We aimed to use contemporary artificial intelligence methods and an MLR model to analyze clinical and experimental data to understand and predict postoperative pain in patients who underwent implant placement.

TABLE 1. Post-operative pain scale.

Score	Percussion Pain
(−)	no pain
(±)	mild discomfort
(+)	Light pain
(++)	pain intermediate to (+++) and (+)
(+++)	acute pain on tapping

II. MATERIALS AND METHODS

Before the start of the study, the Institutional Ethical Board approved the clinical protocol (IHEC/SDC/FACULTY/22/PERIO/318). The participants to be enrolled were briefed regarding the study before obtaining informed consent. (February to April 2022)

A total of 1032 patients (Census approach) indicated for implant surgery were selected as subjects and allocated numbers. Partially edentulous patients who had not taken any analgesic drugs in the past few weeks were included in the study. Patients with diabetes or any immuno-compromised disorders or systemic disease, history of mental disorders, pregnancy or lactation, and patients with allergies were excluded from the study. The selected sample group did not take a prophylactic NSAID before, during, or after the first week of implant surgery. Patients were assessed before, after, and one week following implant surgery.

Regarding the hygienic status of the oral cavity, the OHI-S or the (oral hygiene in-dex-simplified) index was used. Greene and Vermillion [20] proposed the simplified-debris index (DI-S) as well as the simplified calculus index (CI-S), Respectively [20]. They also revised the DI-S and CI-S values and classified them as follows: (0-0.5 = good), (1-2 = medium) & (2.5-3 = bad).

The severity of postsurgical pain and discomfort was categorized according to Table 1,2. Pain evaluation in this experiment was performed using the visual analog scale (VAS) [11]. Patients followed the blinded examiner's instructions to complete the VAS scoring based on personal experiences. Before the doctors chose to reduce subjective errors, a thorough and meticulous examination of the patient's experiences and description of the significance of distinct pain scores was done.

III. DATA NORMALIZATION AND ANALYSIS

Table 2 shows how the parameter data were normalized and counted as the MLR model's input. The output was normalized information regarding both incidence and severity of immediate discomfort post-implant surgery.

To enhance the generalization ability of the MLR model and avoid overfitting, 825 cases (80%) were provided as the training set, while 207 cases (20%) were given for data authentication. In addition, 45 samples were used as controls to determine the model's prediction accuracy mentioned in figure 1.

TABLE 2. Data normalization.

| S.no	Parameter	Normalization processing
1.	Age	20-30 = zero 30-40 = 0.5 40-60 = 0.75 ≥60 = 1
2.	Gender	Male = zero Female = 1
3.	Dental and Oral hygiene status	Good = zero Medium = 0.5 Bad = 1
4.	Location of the teeth involved	Maxilla = zero Mandible = 1
5.	Type of teeth involved	Incisors = zero Canines = 0.5 Premolars = 0.75 Molars = 1
6.	Severity of pain	Absent = zero Slight = 0.2 Mild = 0.4 Moderate = 0.6 Severe = 0.8 Extreme = 1
7.	Mucosal swelling	Absent = zero Present = 1
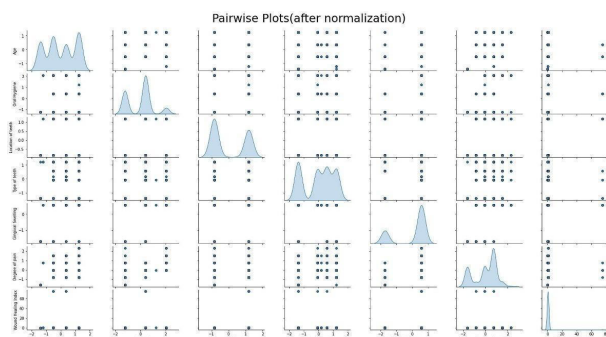
FIGURE 1. Joint distribution after normalization.

IV. ESTABLISHMENT OF MACHINE LEARNING MODEL

Examine impact changes occurring simultaneously in numerous descriptive factors, $x1, x2, \ldots xk$, on an outcome variable, y.

- Examining the individual descriptive variables to evaluate which among them significantly affects y
- Using $x1, x2, \ldots xk$ to predict y

Multiple linear regression is considered an adjunct of simple linear regression when the multivariate model has more than one explanatory variable.(Petrie, Bulman, & Osborn, 2002) This includes information on each individual's readings for the dependent or response variable, 'y', and all of the k descriptive variables, 1 2, …, k. Following the adjustment for the impacts of the other explanatory variables, the aim is to determine the significance of a specific descriptive variable. 'Y' is substantially affected by Xi. Furthermore, by formulating an appropriate model with a specific amalgamation of descriptive variables that can forecast 'y' values, the cumulative impact of these descriptive k variables may be assessed. The multiple linear regression formula prevalent in the population can be described as follows:

$$Y = \alpha + \beta 1\chi 1 + \beta 2\chi 2 + \ldots.. + \beta k\chi k$$

This, in turn, is estimated in the sample by:

$$Y = a + b1\chi 1 + b2\chi 2 + \ldots.. + bk\chi k$$

where,

- 'Y' is the proposed reading for the outcome variable, 'y', for a specific group of readings of descriptive variables, $\chi 1, \chi 2, \ldots, \chi k$.
- A is an unchanging term (the reading of 'Y' when all the χ's are 0), calculating the actual reading, α, in the given population.
- 'bi' (most commonly known as the regression coefficient) is the predicted partial regression coefficient (the mean alteration in 'y' for a unit change in χi, regulating all the other χ's), calculating the actual reading, 'βi' in the given population.

The first phase involves developing a basic prototype consisting of only a single descriptive variable having the highest R2 as opposed to the other single-variable proto-types. In the next phase, if a second variable surpasses the other variables in describing the persisting dispersion, it gets incorporated into the already present prototype, resulting in a discernibly superior model compared to the preceding one. The approach described above is performed multiple times until the new prototype gets significantly enhanced and upgraded to a superior version by including a specific variable.

Suppose processor output via a specific analytical program leaves out confidence intervals for the coefficients. In such a case, the ninety-five percent confidence interval for βi can be estimated as bi ± t0.05 SE (bi), where t0.05 is the %age point of the t-distribution corresponding to a 2-tailed probability of.05, & SE (bi) is the predict-ed standard error of bi.

V. RESULTS

There is a significant association linking the patients' external traits, features of the teeth concerned, clinical aspects, as well as discomfort post-implant surgery. The initial information

TABLE 3. Multi- linear regression model.

Parameter	Error
Root Mean Squared Error	0.1085
Mean Absolute Error	0.0806
Mean Squared Error	0.0118

FIGURE 2. Correlation matrix describing the Gingival Swelling, Oral Hygiene, Age, and Type of Teeth in relation to the intensity of the pain experienced.

regarding the MLR prototype was associated with postoperative discomfort. Table 1 denotes the standardization (data normalization) of the variables mentioned (ranging from zero to 1.5) as follows: patient's dental hygiene status, age, sex, location of teeth, type of teeth, degree of pain, gingival swelling, wound healing index.

A. MODELING THE DATA

The data on postoperative pain was set as the VAS score one week after implant placement.

The given data is nominal and relates between age, sex, oral hygiene, and implant location.

This data represents a relationship between the degree of pain concerning patient factors as follows. Therefore, using mathematical annotations,

X = [Gingival Swelling, Oral Hygiene, Age, Type of Teeth, Location of Teeth]

Y = degree of pain

Where X is nominal data which is further normalized with a standard scalar.

- Count: 1032
- Data: Normalized patient data
- Train size: 825
- Test Size: 207

B. MULTIVARIATE LINEAR REGRESSION

The MLR model's confusion matrix tests the training and validation samples and the total data. It also helps judge the quality of a classifier's output on the data set. The greater the confusion matrix's diagonal values, the better, indicating a significant number of correct predictions. As a result, we predicted that the MLR model might predict implant surgery postoperative pain. We have a deviation of 0.002 in absolute terms-0.08, and square terms are – 0.01.

As per Table 3 the Evaluation of the given model reveals a Root Mean Squared Error of 0.1085 Mean Squared Error is 0.0118. Figure 2 shows the MLR confusion matrix used to examine the authentication and training samples and the collective data. The data set's output is evaluated using a confusion matrix: the higher the confusion matrix's diagonal values, the more correct the predictions. The training sample accuracy and the validation sample accuracy were 90 percent. Also, the test sample prediction model's accuracy was 89.6 %. Hence, the MLR model may predict postoperative pain after peri-implant surgery.
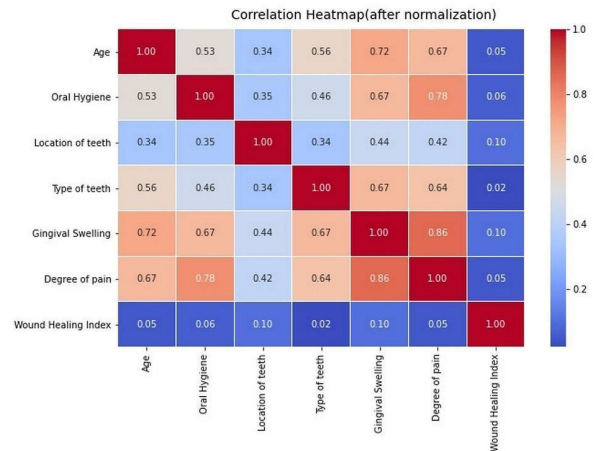
VI. DISCUSSION

The Postoperative pain management after implant placement is vital in optimizing dental care. Pain assessment is often subjective through a patient's self-reporting or the clinician's judgment, resulting in inaccurate pain prediction. Accurate pain prediction would be crucial in providing diagnosis and pain management. AI allows gathering and analyzing multiple expansive data streams regarding a patient to provide a clinical judgment [35] Machine learning can recognize patterns from underlying molecular mechanisms in complex interconnected datasets [17] In this study, we sought to use artificial intelligence methods to examine pain-related data to analyze and map out pain prediction.

In clinical terms, 'pain' can be described as a complicated, multi-faceted sensation that may be affected by various physiological and psychological factors. [36] Most patients experience intense pain after dental operative procedures, which are inflammatory and frequently radiate to the head or face. Literature reveals that the rate of moderate-intense pain can vary from a median (61.9percent) to a high level (89 percent) depending on the subject [4]

After insertion of dental implants, pain and inflammation were measured. In clinical settings, we have found that patients frequently evaluate the efficiency of their treatments based on their subjective feelings. Patients find it difficult to judge the treatment efficacy from a professional standpoint due to a lack of relevant medical knowledge. They may correlate poor pain management with poor quality treatment, leading to dissatisfaction and distrust of the clinician.

Multiple predictors like inflammatory mediators, bone drilling without coolant, and manipulation of bone by surgeons play a role in postoperative surgical pain. In this way, it is impossible to determine how many factors contribute to pain. As pain is a personal and individualized sensation, self-reporting (for example, the Numeric Rating Scale and the Visual Analog Scale) is considered the gold standard to establish its prevalence, absence, and intensity in regular clinical practice [9], [21]. However, it fails to estimate the

severity of post-op pain accurately. Gender, age, allergy history, and surgical retreatment are all factors that influence postoperative surgical discomfort. [4]

Multi-Linear Regression Model (MLR) models use several variables to predict an outcome. It has been used in drug discovery [6], [5], forecasting hormone levels [18], health monitoring [22], and predicting drug efficacy [37]. Several mathematical theories have demonstrated that this network can generate complex non-linear mappings suited to complex mechanisms. Second, this model is professional and reliable parameter selection and data standardization for predicting pain following post-implant surgery.

MLR multi-linear regression model is considered a well-established analytical, educational approach that uses p independent variables $X = [X1|\ldots|Xp]$. These are known as covariates, predictors, or descriptive variables. Using statistical learning techniques, multivariate analysis is used for inferring relationships between dependent and independent variables (X1 & Xp). A predictor is a variable used to explain a dependent variable (Y). The least-squares approach suffers from several issues as the no. of explanatory variables, p, grows, including forecast accuracy loss and interpretation difficulties. To solve these issues, a model with a few "essential" variables that can provide a reasonable result justification and high generalization while losing a few specifics is ideal. The prototype selected is responsible for determining subsets of descriptive variables that must be "chosen" for adequately describing the response 'Y,' resulting in a settlement known as the 'bias-variance trade-off.' It is the same as choosing between 2 linear regression prototypes (that is, using an amalgamation of variables) [1]

While it is essential to understand that using significantly fewer variables may cause "data under-fitting," described as having low predictive accuracy, slight variance as well as high bias; choosing a high number of variables may result in "data overfitting" characteristic of substandard predictive accuracy, considerable variation, and slight bias. Gradual linear regression is a subset regression analysis that attempts to solve this challenge.

There is a complex non-linear relationship. Clinical experience alone is insufficient to predict the risk of postoperative discomfort. As a result, there is a need for an advanced AI tool to assess the non-linear relationship properly. MLR's key benefit is its ability to examine many covariates without analytical modelling and successfully cope with indeterminate situations. MLR also can learn from input data, which is an important feature [38]

The probability of moderate or severe discomfort following implant surgery increases with age. Based on gender, notable dissimilarities can be observed in the experimental and clinical responses to pain between males and females, where the women have a considerably higher risk of postoperative pain. [15] Genetic background is also linked to the patient's personal qualities. Still, it was excluded from this study since the use of complex genotypes as factors for predicting pain after implant surgery is relatively complex even

now. Simultaneously, the no. of implants, type, the affected area, occlusal discrepancies, and other parameters are also responsible for postoperative pain. Furthermore, the choice of sutures and equipment was not considered after surgical suture removal [15]

Postoperative pain psychological variables cover a broad spectrum of elements. [39] Studies failed to consider psychological factors such as the effect of anxiety on pain after implant surgery [23]. In this study, we used the MLR model to input one potential variable from the patient's data, dental and surgical characteristics. Due to an extensive training sample, the impact of the selection of parameters, data standardization, and the selection of variables on the final result is relatively small. Other elements that may affect postoperative pain but are not covered by the criteria, such as bone drilling protocols, coolant, sharp drills, and surgeon manipulation, are classified under the same control. Furthermore, to prevent intra and inter-examiner bias, the examiners were thoroughly trained before the study to ensure they had a shared knowledge of the diagnostic criteria.

This experiment selected eight possible variables in the patients and dental characteristics as the MLR prototype's input variables. Other factors that may contribute to postsurgical pain were not considered. In some clinical scenarios, the patient clinically experienced pain even though the prototype did not predict any discomfort, which is a limitation. Postoperative psychological factors cover sadness, anxiety, and somatization. Most studies fail to consider these psychological factors and their impact on postsurgical pain. Further research with diverse datasets and an extended follow-up protocol considering psychological factors can advance pain prediction algorithms.

Unlike humans, AI is only limited by processing power. It can analyze troves of data to recognize imperceptible patterns and provide insights into diagnosis. While machine learning may never replace a clinician, AI will serve as a new tool in innovation and patient care, with algorithms eventually surpassing human judgment. Future studies in cooperation with data scientists can serve to interpret the complexities of pain, mapping predictors, variables and predicting the type of pain.

VII. CONCLUSION

The current study examined the feasibility of pain prediction in implant patients using artificial intelligence. Using 825 cases as a training set, our prototype predicted postoperative pain with 89.6 % accuracy. The current study expands the knowledge base on AI-based pain prediction and opens new avenues for research. Artificial intelligence will inevitably impact patient care, from postoperative care to pain management. Future research and evolving datasets will provide avenues to understand better the complex interplay between physical and psychological factors that affect pain perception. While today machine learning is limited to narrowly defined research, future possibilities for the application of AI in pain management are manifold.

Unlike humans, AI is only limited by processing power. It can analyze troves of data to recognize imperceptible patterns and provide insights into diagnosis. While machine learning may never replace a clinician, AI will serve as a new tool in innovation and patient care, with algorithms eventually surpassing human judgment. Future studies in cooperation with data scientists can serve to interpret the complexities of pain, mapping predictors, variables and predicting the type of pain.

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