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ORIGINAL ARTICLE

Predictive Machine learning Models for necessity Supplemental Anesthesia in Endodontic treatment

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ABSTRACT

Purpose: In cases of irreversible pulpitis, controlling intraoperative endodontic discomfort is extremely difficult, and patient satisfaction plays a big part in this. In order to forecast a diagnostic's and a treatment's outcome, machine learning (ML) has recently been implemented in the fields of medicine and dentistry. The goal of this work was to create machine learning (ML) models that could predict the need for further anesthesia.

Methods: According to inclusion and exclusion criteria, this study included 128 individuals with endodontic discomfort. All patients underwent a clinical evaluation and endodontic diagnostic procedures. All interpretation results were entered into a prepared data sheet. All info were statistically evaluated using Github software version ydata-profilling vv4.1.2, configuration config.json, was employed to review the explanatory data for machine learning models for all examination and investigation aspects. By using Pearson correlation, chi 2, Random Forest, and LightGBM, the final feature importance was determined. 20% of the test set and 80% of the train set are observation sets used to build models. Logistic regression F1 and k-nearest neighbors (KNN) F1 were used to assess the performance of the ML model on the train and test sets.

Results: For Machine learning models, 11 of the 20 features—such as pulp stone or calcification of the pulp space, pain duration, age, percussion, palpation, response persistent after EPT, dental history, curved root canal, pain persistent after a cold test, and pain severity during a cold test—were important. In logistic regression, F1 for the train set was 0.793, while for the test sets, it was 0.878. Regression using a logistic model had an accuracy of 0.81. KNN F1 for train was 0.781, while for test it was 0.829. The Machine learning model's k-nearest neighbors (KNN) F1 accuracy was 72.86.

Conclusion: The trained machine learning models can predict if further anesthetic will be required during endodontic treatment based on the specific feature.

Keywords: Machine learning, Supplementary Anesthesia, Logistic regression, KNN algorithm, Clinical examination, feature importance.

Introduction

Pain is the primary factor driving patients to seek endodontic treatment. Endodontic therapy may be avoided because of the direct relationship between anxiety and pain.[1] In order to be able to control the association between pain aversion and avoidance of endodontic treatment, a patient's self-efficacy is a key factor.[2] Treatment-related pain was substantially correlated with both treatment avoidance and predicted discomfort.[2] Overall satisfaction with endodontic therapy was significantly influenced by how intraoperative discomfort was managed.[3] Due to self-efficacy, a lowered pain threshold, and pulp inflammation, patients with symptomatic irreversible pulpitis would not obtain effective pain management during endodontic therapy.[4,5] The necessity of supplementary anesthesia for pain control during endodontic treatment was 22-90% of patients without considering of mandibular and maxillary teeth.[6,7]

The purpose of a pulp sensibility test is to extrapolate and assess the vitality and state of pulp health through qualitative sensory manifestations. When a pain-producing excessive response occurs, pulpitis is present.[8] This discovery helps to explain how the pulp reacts to stimuli and the pain associated with pulpitis. Adhibit, a mechanical sensory test with diagnostic value that includes percussion and palpation, exhibits peripheral and central sensitization-induced mechanical allodynia coming from inflamed and hypersensitive pulpal neuronal afferents.[9] Periodontal charting in detail, including measurements of periodontal pocket depth, isolated bone loss, and attachment loss, is crucial for assessing the effectiveness of treatment.[10] When teeth had periodontal pockets, the pulp's response was noticeably more pronounced.[11]

Most people believe that tooth pulp defense mechanisms like pulp stones and calcification are the cause of irritation and inflammation. Additionally, systemic conditions, including cardiovascular disease and diabetes mellitus, are linked to pulp stones.[12,13] Pulp stones appear as radiopaque lumps on radiographs in the coronal or radicular regions of the pulp. Radiographic evaluation can be done during routine endodontic diagnosis procedures to check for pulp calcification, curved canals, lamina dura loss, and alveolar bone loss around the tooth.

The effects of local anesthesia include a reduction in nerve ending stimulation or an inhibition of the conduction process in peripheral nerves.[14] The most common method of pain management during endodontic and restorative procedures is local anesthesia. Pulpal anesthesia can be particularly challenging; failure rates during dental procedures have been reported to range from 47 to 91% for mandibular teeth, or around 14% (1 in 7 persons).[15,16] As a result, physicians are contemplating additional local anesthesia as an adjuvant therapy to enhance painless endodontic and restorative care. According to several researchers, the cold test may be a useful and reliable tool for anticipating pulpal anesthesia .[17]

Painless procedures increase confidence between the doctor and patient, preventing the patient from dreading and putting off treatment. Therefore, a model that can aid the dentist in making predictions is required, particularly for pain management. Machine learning (ML) model has already shown potential for predicting, diagnosis, detecting, containing and therapeutic motoring of diseases.[18,19]

The ability to learn from experience rather than merely commands, one of the fundamental principles of artificial intelligence (AI), is encompassed by machine learning (ML), a subset of AI. ML algorithms automatically evolve from their output, create the desired results, and learn from it.[20] Providing labeled sample inputs that represent the desired results to training algorithms is a key component of the supervised learning subfield of machine learning. Supervised machine learning (SML) investigates techniques that produce general hypotheses to address a problem and make future predictions.[21] The goal of this study was to develop supervised ML models that could predict the necessity of supplementary anesthesia for individual patient.

Materials and Methods

Dataset

The Department of Conservative Dentistry and Endodontics at Chattagram International Dental College & Hospital provided the dataset for patients with supplemental needs. 20 features, including the binary target feature that determines if a patient need supplement anesthetic, have been gathered from 127 patients. The dataset contains 19 dependent variables, such as sex, age, previous dental history, medical history, pain severity on a visual analogue scale (VAS), length of time experiencing pain, percussion, palpation, mobility, and more. involvement of the periodontal ligament, Response, or pain in the electrical pulp tester (EPT), Pain or sensibility during the cold test, Pain or sensibility persists after the cold test, persistent pain or reaction following EPT, current EPT pass unit, curved canals, pulp stones or calcification, enlargement of the periodontal ligament space, lamina dura loss, and 1 independent variable is whether a supplement is needed. Data was sent for exploratory data analysis. (Table 1& 2)

Table 1: Explanatory data analysis of categorical variables including boolen variables.

Feature	Yes (1)/ Male	No (0)/Female
Patient	65 (51.18%)	62 (48.82%)
Dental History	29 (22.83%)	98 (77.17%)
Medical history	37 (29.13%)	90 (70.87%)
Percussion	83 (65.35)	44 (34.65%)
Palpation	36 (28.35%)	91 (71.65%)
Mobility	31 (24.41%)	96 (75.59%)
Periodontal involvement	38 (29.92%)	89 (70.08%)
Curved root canal	34 (26.77%)	93 (73.23%)
Pulp stone or and Calcification	41 (32.28%)	86 (67.71%)
Periodontal ligament space	44 (34.65%)	83 (65.35%)
Lamina Dura loss	38 (29.92%)	89 (70.08%)
Need Supplement	84 (66.14%)	43 (33.86%)

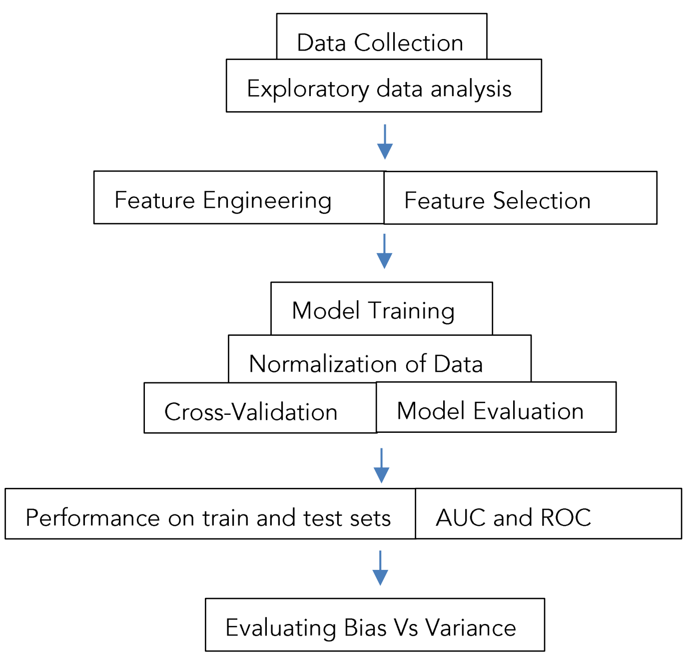
Table 2: Explanatory data analysis of numerical variables'

	Mini-Maxi	Median	Mean ± SD	CoV
Age	16 – 68	33	36.46 ± 12.14	0.332
Pain (VAS)	1 – 10	6	6.60 ± 1.76	0.267
Pain Duration (days)	0 – 210	7	31.22 ±51.97	1.664
Pain in Cold test (VAS)	0 – 10	7	6.60 ± 2.50	0.379
Persistent (sec) of Pain after cold test (VAS)	0 – 50	17	16.10 ± 8.72	0.541
Response of EPT (VAS)	0 – 10	5	5.0 ± 1.99	0.399
Persistent EPT response (sec)	0 – 37	7	8.82 ± 6.37	0.721
EPT current pass	0 – 80	35	33.82 ± 17.16	0.507

Supervised Machine Learning Algorithms

Feature Engineering: It was important to encode the categorical features into numeric features because most ML algorithms can operate on numeric data. We utilized one-hot encoding to transform the categorical features into indicator variables, also known as dummy variables, because all the categorical features in the data set are nominal, i.e., their classes have no meaning order. For each class in a categorical feature, one-hot encoding generates a new dummy variable, where a value of '1' for the dummy variable denotes the presence of the class and a value '0' denotes its absence.

Flow chart:



Feature Selection

Feature selection is a technique for excluding the significant characteristics from the dataset as well as those features that are present but not all equally significant. Some features have no impact whatsoever on the result. We want to decrease the data before feeding it to the training model, thus that's why. By using Pearson's correlation, Chi-square, Random Forest, and LightGBM, we were chosen as the most important feature.

The test statistic used to determine the statistical association or relationship between two continuous variables is called the Pearson's correlation coefficient. It provides details on the size of the association or correlation as well as the relationship's slant. The strength is represented by a number that ranges from -1 to 1. When a person's correlation coefficient (r) value is greater than 0.5, 0.3 to 0.5, 0 to 0.3, 0, 0--0.3, -03 to -0.5, or less than -0.5, the relationship between two variables is shown to be strong and positive, moderately strong, and positive, weakly positive, none, weakly negative, moderately strong negative, or strongly negative. To choose the variables, we must define a threshold of an absolute value, let's say 0.5.

When a dataset contains categorical features, the Chi-square Test is utilized. Each feature's relationship to the target is analyzed using Chi-square, and the desired number of features with the highest Chi-square scores are chosen. The following prerequisites must be satisfied: the variables must be categorical, sampled independently, and values must have an anticipated frequency to properly apply the Chi-squared to evaluate the relationship between different features in the dataset and the target variable.

The average impurity decrease derived from all the decision trees in the forest can be used to quantify the feature relevance in Random Forest. No matter if the data is linear or non-linear, this holds true. Here, the relevance of each characteristic was determined using Python programming.

Gradient Boosting Algorithm As indicated in the equation below, the gradient boosting technique trains a predictive model by integrating M additive three models (T0, T1, ...Tn) to forecast the outcomes:

$$f(x)=\sum_{m=0}^{m} f_m(x)$$

By decreasing the anticipated generalization error L, as stated in the equation below, the ensemble model can be improved.

$$L = \sum_{i}^{n} (y_i - \hat{y}_i)2.$$

Finding top feature by comparing of feature selection techniques: To identify the most important features for a machine learning model, we utilized the Pearson's correlation, Chi-square, Random Forest, and lightGBM tests. Our machine learning model includes every feature that in three experiments demonstrated importance.

Model Training

Train/ Test Split

We reserved 80% of the observations for the train set and 20% of the observations for the test set.

Normalization of Data

It's possible for input variables to have distinct scales because of their different units (such as feet, kilometers, and hours). The difficulty of the problem being modelled could be exacerbated by differences in the scales across the input variables. A model may learn huge weight values because of having large input values, such as a spread of hundreds or thousands of units. Large weight values indicate that the model is unstable, which means that it may perform poorly during learning and be sensitive to input values, leading to a higher generalization error. Standardization shifts the distribution to have a mean of zero and standard deviation (SD) by scaling each input variable separately by deducting the mean (called centering) and dividing by the SD.

Cross-Validation

To cross-validate the models and fine-tune the hyperparameters, we used GridSearch cross-validation. The logistic regression model and K closest neighbor (KNN) underwent gridsearch cross-validation.

Model for logistic regression: The output of a dependent variable that is categorical is predicted by logistic regression. The value must therefore be categorical or discrete. In our foreseeable model, the choice is YES or NO. We used Python to implement logistic regression (Binomial).

Steps in Logistic Regression were followed in below –

1. Data Pre-processing step
2. Fitting Logistic regression to the training set.
3. Predicting the result.
4. Test accuracy of the result (creation of confusion matrix)
5. Visualization the test set result.

K nearest neighbor (KNN): One of the simplest supervised learning-based machine learning algorithms is KNN. Based on similarity, K-NN algorithms store every accessible data point. This means that using the K-NN method, fresh data can be quickly sorted into a category that fits it. Steps to implement the K-NN algorithm were followed in below-

1. Data Pre-processing step.
2. Fitting the K-NN algorithm to the training set.
3. Predicting the test result.
4. Test accuracy of the result (creation of confusion matrix).
5. Visualization the test set result.

Model Evaluation

Performance on the Train and Test Sets: After training and cross validating the models, we used them to predict on the Test Set. Using the same F1 and accuracy metrics that I used to assess the models during cross-validation, I assessed the model's performance on the test set.

Area Under the Curve (AUC) and Receiver operating characteristic Curve (ROC)

Measurements for categorization issues were made using the AUC and ROC curves at various threshold settings. AUC is a probability curve, and ROC is the degree or measure of separability. It was revealing the extent of the model's ability to discriminate between classes. The model is more accurate at classifying 0 classes as 0, and classifying 1 class as 1, the higher the AUC.

Evaluating Bias Vs Variance

To objectively determine the degree of Bias and Variance exhibited by the models, we used the guidelines presenting below.

Bias:

- High Bias: F1 <0.70
- Medium Bias: F1 > 0.70 to <0.90
- Low Bias: F1 >0.90

Variance:

- High variance: (% difference in F1 between train and test set) > 25%.
- Medium variance: 5% < (% difference in F1 between train and test set) <= 25%.
- Low variance: (% difference in F1 between train and test set) <= 5

Predictive Machine learning model:

There was 20 variables and 127 observations in this study. Among those 11 variables were categorical 8 numeric and 1 Boolean (Table 1 & 2, Figure -I). There is not every one feature does carry same important. Important feature had been selected by Pearson's correlation, chi-square, random forest and light GBM. We were selected 11 final features for machine learning model including target variable (need supplement) those were showing positive at least three tests (Figure-II). Before the development of the model, the correlation co-efficient (r) analysis between the various dependent and independent features was carried out to determine a strong relationship between each other's. (Table 3 & 4) All data were normalized and standardization (Table 5). The dataset for need supplement or not been partitioned into training and test sets. Therefore, the model was trained the models with 80% training and tested with the remaining 20% of the dataset. Logistic regression model and K nearest neighbor machine learning classification algorithms to predict whether the necessity of supplement anesthesia for pain control during endodontic treatment. Having trained and cross-validated the models, we then used the models to make predictions on the test set. We evaluated the performance of the models on the test set using the same F1 and accuracy metrics used to evaluate the models during cross-validation. AUC- ROC curve was used to performance measurement for classification problems at various threshold settings. We also determine the degree of bias and variance exhibited by the models.

Figure I: 20 variables were selected for explanatory data analysis

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 127 entries, 0 to 126
Data columns (total 20 columns):
 #   Column                                  Non-Null Count  Dtype
---  ------                                  --------------  -----
 0   Patient                                 127 non-null    object
 1   Age                                     127 non-null    int64
 2   Dental History                          127 non-null    int64
 3   Medical History                         127 non-null    object
 4   Pain (VAS)                              127 non-null    int64
 5   Pain ( Duration) days                   127 non-null    int64
 6   Percussion                              127 non-null    int64
 7   Palpation                               127 non-null    int64
 8   Mobility                                127 non-null    int64
 9   PDL involvement                         127 non-null    int64
 10  Curved Canal                            127 non-null    int64
 11  Pulp stone or and Calcification         127 non-null    int64
 12  PDL space                               127 non-null    int64
 13  Lamina Dura                             127 non-null    object
 14  Cold test ( VAS) Before anaesthesia     127 non-null    int64
 15  Cold test (Duration) Before anaesthesia 127 non-null    int64
 16  EPT ( VAS) before anaesthesia           127 non-null    int64
 17  EPT current pass                        127 non-null    int64
 18  EPT (Duration) before anaesthesia       127 non-null    int64
 19  Need Supliment                          127 non-null    object
dtypes: int64(16), object(4)
memory usage: 20.8+ KB
```

Figure II: Features responses to feature selection algorithm.

Finding Top Features by comparing of Feature Selection Techniques

	Feature	Pearson	Chi-2	Random Forest	LightGBM	Total
1	Pulp stone or and Calcification	True	True	True	True	4
2	Pain (Duration) days	True	True	True	True	4
3	Age	True	True	True	True	4
4	Percussion	True	True	False	True	3
5	Palpation	True	True	False	True	3
6	EPT (Duration) before anaesthesia	True	True	True	False	3
7	Dental History	True	True	False	True	3
8	Curved Canal	True	True	False	True	3
9	Cold test (Duration) Before anaesthesia	True	False	True	True	3
10	Cold test (VAS) Before anaesthesia	True	False	True	True	3
11	Pain (VAS)	False	False	True	True	2
12	Mobility	False	True	False	True	2
13	Medical History_DM, HTN	True	True	False	False	2
14	Medical History_DM	True	True	False	False	2
15	Medical History_0	True	True	False	False	2
16	EPT current pass	True	False	True	False	2
17	EPT (VAS) before anaesthesia	True	False	True	False	2
18	Patient	False	False	False	True	1
19	PDL space	False	False	False	True	1

Table 3 : Pearson's Correlation coefficient (r) of 20 variables

	Age	Pain (VAS)	Pain Duration	Pain in cold	Pain persists	EPT response	EPT Current	EPT response	Patient	Dental history	Medical history	Percussion	Palpation	Mobility
Age	1.000	0.038	0.401	-0.166	0.272	-0.111	0.452	0.155	0.131	0.373	0.336	0.278	0.069	0.348
Pain (VAS)	0.030	1.000	-0.284	0.242	0.317	0.083	0.019	0.246	0.237	0.173	0.000	0.424	0.669	0.000
Pain Duration	0.401	-0.284	1.000	-0.064	0.224	-0.055	0.421	0.006	0.065	0.386	0.345	0.305	0.234	0.521
Pain in cold	-0.166	0.242	-0.064	1.000	0.398	0.616	-0.376	0.233	0.000	0.199	0.176	0.224	0.387	0.189
Pain persists after cold	0.272	0.317	0.224	0.398	1.000	0.138	0.143	0.575	0.018	0.278	0.269	0.298	0.179	0.302
EPT response	-0.111	0.083	-0.055	0.616	0.138	1.000	-0.304	0.269	0.000	0.179	0.176	0.157	0.251	0.532
EPT Current pass	0.452	0.019	0.421	-0.376	0.143	-0.304	1.000	0.127	0.000	0.201	0.174	0.174	0.000	0.000
EPT response persists	0.155	0.246	0.006	0.233	0.575	0.269	0.127	1.000	0.000	0.164	0.000	0.261	0.224	0.000
Patient	0.131	0.237	0.065	0.000	0.018	0.000	0.000	0.000	1.000	0.000	0.165	0.000	0.000	0.134
Dental history	0.373	0.173	0.386	0.199	0.278	0.179	0.201	0.164	0.000	1.000	0.321	0.301	0.155	0.220
Medical history	0.336	0.000	0.345	0.176	0.269	0.176	0.174	0.000	0.165	0.321	1.000	0.157	0.191	0.333
Percussion	0.278	0.424	0.305	0.224	0.298	0.157	0.174	0.261	0.000	0.301	0.157	1.000	0.771	0.443
Palpation	0.069	0.669	0.234	0.387	0.179	0.251	0.000	0.224	0.000	0.155	0.191	0.771	1.000	0.344
Mobility	0.348	0.000	0.521	0.189	0.302	0.532	0.000	0.000	0.134	0.220	0.333	0.443	0.344	1.000
PDL involve	0.506	0.000	0.419	0.218	0.451	0.301	0.338	0.000	0.000	0.129	0.459	0.530	0.242	0.483
Curved canal	0.086	0.000	0.082	0.217	0.234	0.000	0.122	0.246	0.000	0.000	0.161	0.248	0.000	0.000
Pulp stone or calcification	0.520	0.000	0.427	0.109	0.398	0.000	0.367	0.297	0.000	0.230	0.510	0.144	0.160	0.239
PDL Space	0.429	0.104	0.401	0.146	0.418	0.315	0.369	0.000	0.000	0.196	0.426	0.514	0.243	0.406
Lamina dura loss	0.487	0.076	0.421	0.206	0.458	0.233	0.444	0.000	0.000	0.222	0.443	0.533	0.282	0.401
Need Supplements	0.358	0.000	0.245	0.207	0.291	0.271	0.294	0.281	0.000	0.147	0.232	0.073	0.149	0.127

Need Supplements	Lamina dura loss	PDL Space	Pulp stone or	Curved canal	PDL involv
0.358	0.487	0.429	0.520	0.086	0.506
0.000	0.076	0.104	0.000	0.000	0.000
0.245	0.421	0.401	0.427	0.082	0.419
0.207	0.206	0.146	0.109	0.217	0.218
0.291	0.458	0.418	0.398	0.234	0.451
0.271	0.233	0.315	0.000	0.000	0.301
0.294	0.444	0.369	0.367	0.122	0.338
0.281	0.000	0.000	0.297	0.246	0.000
0.000	0.000	0.000	0.000	0.000	0.000
0.147	0.222	0.196	0.230	0.000	0.129
0.232	0.443	0.426	0.510	0.161	0.459
0.073	0.533	0.514	0.144	0.248	0.530
0.149	0.282	0.243	0.160	0.000	0.242
0.127	0.401	0.406	0.239	0.000	0.483
0.000	0.754	0.732	0.252	0.015	1.000
0.000	0.230	0.276	0.000	1.000	0.015
0.397	0.252	0.205	1.000	0.000	0.252
0.000	0.878	1.000	0.205	0.276	0.732
0.000	1.000	0.878	0.252	0.230	0.754
1.000	0.000	0.000	0.397	0.000	0.000

Table 4: r- value and correlation coefficient of final feature selection for ML model

SN	Dependent Variable	Independent variable	r- value	Correlation coefficient relationship
1	Pulp stone & or Canal calcification	Need supplement anesthesia	0.397	A moderate positive correlation coefficient
2	Age	Need supplement anesthesia	0.358	A moderate positive correlation coefficient
3	EPT current pass (unite)	Need supplement anesthesia	0.294	A weak positive correlation coefficient
4	Pain Persist after cold	Need supplement anesthesia	0.291	A weak positive correlation coefficient
5	EPT response persist	Need supplement anesthesia	0.281	A weak positive correlation coefficient
6	EPT response scale	Need supplement anesthesia	0.271	A weak positive correlation coefficient
7	Pain Duration	Need supplement anesthesia	0.245	A weak positive correlation coefficient
8	Pain in Cold	Need supplement anesthesia	0.202	A weak positive correlation coefficient
9	Dental History	Need supplement anesthesia	0.147	A weak positive correlation coefficient
10	Palpation	Need supplement anesthesia	0.149	A weak positive correlation coefficient

Table 5: Data normalization and standardization of final selective feature for ML

	0	1	2	3	4
Age	0.853624	-1.308012	1.934441	-0.809173	-1.058592
Pain Duration (days)	-0.479279	-0.035176	1.123352	1.123352	-0.575823
Dental History	1.951800	-0.512348	-0.512348	-0.512348	-0.512348
Percussion test	1.371916	-1.210012	1.371916	0.511273	-1.210012
Palpation	1.614665	-0.619324	-0.619324	-0.619324	-0.619324
Pain in cold test (VAS)	0.602527	0.217367	0.217367	-0.938112	-0.552952
Pain persists after cold test (sec)	0.449482	-0.997012	1.228362	0.672019	-0.997012
Persists EPT response (sec)	-0.103195	-0.943732	0.569235	-1.111840	-1.111840
Pulp stone or and Calcification	1.538397	-0.650027	1.538397	-0.650027	-0.650027
Curved Canal	-0.619324	-0.619324	1.614665	1.614665	-0.619324

Results:

Logistic regression F1 = 0.793 for the train set and 0.878 for the test set, and logistic regression accuracy = 0.723 for the train set and 0.808 for the test, were determined to be the models' performance on the test and train sets. The accuracy of the models was 0.81, according to the classification report using logistic regression (table 6). Accuracy has been determined to be 0.81 in the logistic regression confusion matrix (Table 7); KNN F1 was o.781 for train and 0.829 for test; and KNN accuracy was 0.732 for train and 0.731 for test (Table 6). The performance of the classification issue was evaluated at various threshold values using the AUC-ROC curve. The values for the ROC and AUC curves were 0.7286 (Figure IV). The observation was that the ML model will be able to distinguish between positive and negative classes (Figure III).

In this study, predictive machine learning models for necessity of supplement anesthesia based on logistic regression, and K nearest neighbor algorithms. The absolute value of the Pearson's correlation coefficient, chi-square metric between target and numerical features were evaluated. Random Forest algorithms was used for selecting feature based on feature importance. The RF, the final feature importance is the average of all decision tree feature importance. We also used Light GBM for feature importance attribute. We select 10 features for our machine learning (ML) model dependent on response to feature selection algorithms (table 4). Selected feature must have response to at least three feature selection algorithms. All final selected feature showed weak to moderate correlation coefficient (r- value) relationship (Table 4) with target feature that means need supplement anesthesia. Pulp stone or and calcification (r- value 0.397), age (r- value 0.358), EPT current pass (r- value 0.294), pain persist after cold (r- value 0.291), EPT response persist (r- value 0.281), EPT response (r- value 0.271), Pain duration (r- value 0.245), Pain in cold (r-value 0.202), Dental history (r- value 0.147), Palpation (r- value 0.149) were selected as final feature of ML model (Table 4).

Table 6: Performance on Train and Test set in Logistic regression algorithms and K-NN algorithms

ML algorithm	Train	Test
Logistic regression F1	0.793	0.878
Logistic Regression accuracy	0.723	0.808
KNN F1	0.781	0.829
KNN accuracy	0.732	0.731

Table 7: Logistic regression classification report

	Precision	Recall	F1 score	Support
0	0.50	0.60	0.55	5
1	0.90	0.86	0.88	21
Accuracy			0.81	26
Macro avg	0.70	0.73	0.71	26
Weighted avg	0.82	0.81	0.81	26

Figure iii: True Positive Rate (TPR) and False Positive Rate (FPR) in every threshold.

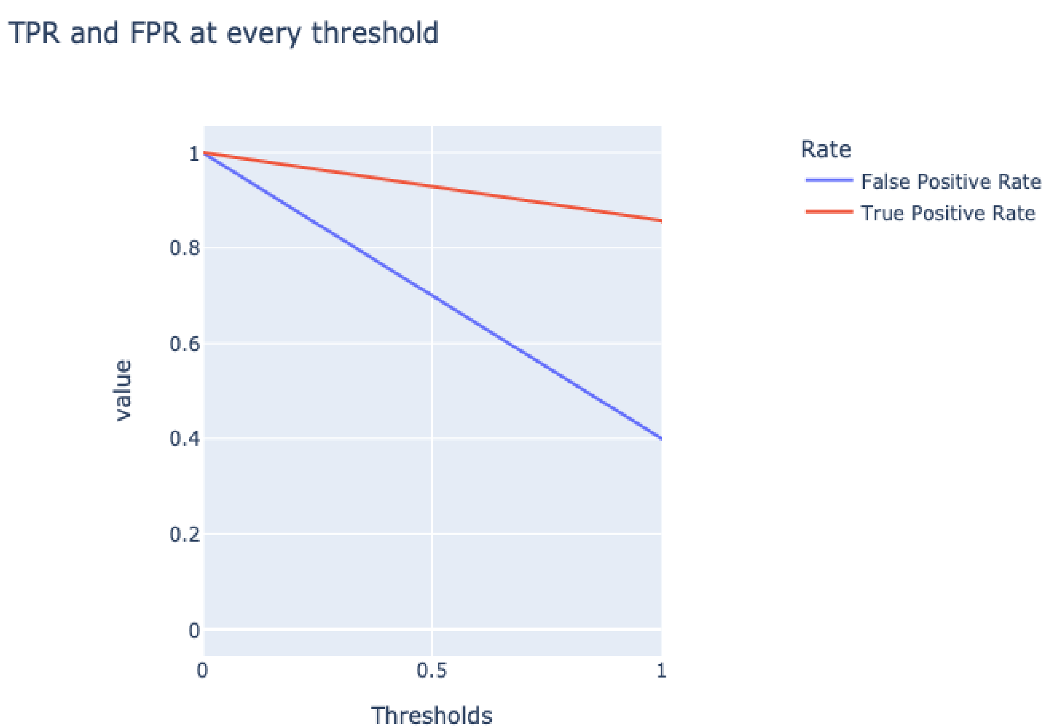
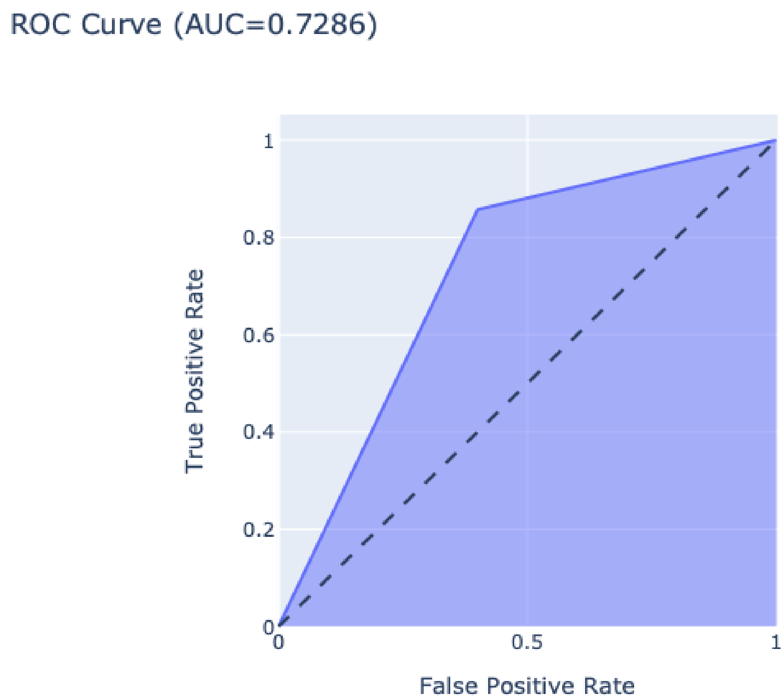


Figure IV: ROC curve AUC showed machine learning model can predict 73% accuracy to predict.



Discussion

Because it is more difficult to manage pain in irreversible pulpitis, both patients' and the operator's confidence are lowered during endodontic therapy. In order to help with appropriate intraoperative pain control and ideal anesthetic procedural techniques, new trustworthy tools for prediction of future extra anesthesia necessary right before commencement of the surgery are critically needed. ML models enable efficient analysis of multiple variables with linear or non-linear correlations and even the discovery of novel interactions. Furthermore, after being trained, the current models can be improved over time by utilizing new clinical data. In spite of the challenging endeavor, we created a model utilizing KNN and logistic regression to foretell the requirement for extra local anesthesia for successful, painless endodontic treatment.

In the current investigation, the logistic regression accuracy and KNN accuracy performances of the ML models were 0.72 and 0.73 in the train and 0.81 and 0.731 in the test, respectively. Because logistic regression can interpret model coefficients as markers of feature relevance and is simpler to build, interpret, and train than other methods, we utilized it for model training and testing.[22] In this work, we used the Pearson coefficient, Chi-2, and Random Forest LightGBM to evaluate the significance of the eleven features. The accuracy of the logistic regression confusion matrix we constructed was 0.81. The assumption of linearity between dependent variables and independent variables, however, is the main drawback of logistic regression.[22] Because KNN predicts a target variable using one or more independent variables, we employed it to get around the constraint of logistic regression.[23] The model used in this study is around 70% effective at differentiating between positive and negative classes. To avoid overfitting and underfitting, the bias and variance in our suggested ML model were assessed.

It's interesting to note that the final feature chosen for the ML model from the clinical research data presented had previously been proven to significantly affect the efficacy of anesthesia. Age, the length of pain, and pulp stone formation or calcification of the pulp space were all found to be quite significant in the study that was presented. According to earlier research, patients with pulp stones had considerably greater anesthetic failure rates in both the first and second maxillary molars on both the right and left sides.[24] Another aspect of pain that is crucial for the ML model is its duration. We discover a significant Pearson coefficient association (0.521) between tooth mobility and the study at hand. Due to periodontitis' enhanced mechanical allodynia and high level of pain intensity and duration, central sensitization (CS) has been created .[25] Failures of local anesthetics were influenced by central sensitization.[26] It has been demonstrated that central sensitization contributes to the degree of pain during percussion and palpation.[26] The severity of pain and palpation (0.669), loss of lamina and periodontal involvement (0.754), periodontal space (0.878), and the Pearson correlation coefficient were all highly correlated with one another and may also be finding criteria for MA.

A significant association was found between the degree of pain experienced during the cold test and the EPT reaction (PCC = 0.616), as well as between the degree of pain experienced (PCC = 0.575) after the cold test and the persistence of the EPT response (Table 3). Severe, ongoing discomfort following exposure to cold stimuli is one of the important signs for a clinical diagnosis of irreversible pulpitis.[27] In pulp sensibility tests, the cold test and the EPT serve as stimuli for evaluating the response in order to determine the pulp's state of health.

In the presented history, there was a high correlation between medical history and pulp stone or calcification of pulp space (0.510) and pulp stone or calcification of pulpal space (0.520) with age (table 3). 29.13% of patients included in this study had medical history like diabetes militias, cardiac problem, hypertension (table 1). An intriguing phenomenon related to an altered state of inflammation is pulp stones, which were observed more frequently in diabetic patients and cardiac patients.[28,12]

In this study, we performed an ML model to simplify the process of predicting the need for further anesthesia during endodontic treatment. Although showing promising results, this study has some limitations, like small data for successful anesthesia, which is attributed to missed predictions and leads to bias in measuring performance metrics. However, this problem could be overcome by using the synthetic minority oversampling technique (SMOTE) and enlarging the minority dataset continuously in the future.[22] To ensure data credibility, both endodontists included in this study have more than ten years of experience in the field of endodontics to minimize bias. Future research should be enrolled on the cognitive dimensions of pain, pain perception, and treatment satisfaction to determine the impact of pain-free endodontics on the overall performance of models.

Conclusion:

Through the use of specific features such as pulp stones or pulpal space calcification, pain, age, percussion, palpation, persistent response after EPT, dental history, curved canals, persistent pain after a cold test, and severity of pain after a cold test, the trained logistic regression analysis and KNN algorithm models can predict the need for additional anesthesia in endodontic treatment. The ML algorithm may be used to forecast intraoperative pain management techniques. Patient self-efficacy with regard to endodontic therapy has consequently increased. A youthful dentist can also anticipate the need for less time-consuming further supplementary anesthetics with ease.

Conflict of Interest Statement:

All authors deny any conflicts of interest related to study

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