치의학 석사 학위논문

Prediction of oral implant prognosis through machine learning methods:

- Keys to implant success-

Machine learning method를 이용한 임플란트 예후 예측 요소

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Abstract

Prediction of oral implant prognosis through machine learning methods:

- Keys to implant success-

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Purpose: Despite the high success rate of oral implants, usually described as osseointegration, the practitioner occasionally encounters difficulties caused by trade-offs between various factors during surgery. The purpose of this study was to discover the most significant factors predicting implant success using non-traditional statistical analysis.

Materials and Methods: The study was based on a systematic search of chart files at Seoul National University Bundang Hospital from June 2004 to October 2005. Oral and maxillofacial surgeons inserted 667 implants in the

mouths of 198 patients after consultation with a prosthodontist. The implants were judged as favorably or unfavorably placed and the associated outcome was assessed 1 year after treatment by a prosthodontist from a biomechanical point of view. We processed descriptive evaluations for several features in binary form for the analysis. Unfortunately, some cases were excluded due to lack of information during this process. In this study, we used the machine learning method of a decision tree model and a support vector machine for analysis.

Results: We identified mesio-distal position of the fixture as the most significant factor determining the prognosis of the implant. Both of the machine learning methods yielded this result.

Discussion: The strength of the machine learning method is that it can be applied to a small sample size. To verify the conclusion of this study, traditional statistical tools could be applied with large samples.

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Keywords **:** dental implant, implant prognosis, machine learning method, decision tree model, support vector machine

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Introduction

Implant-supported rehabilitation consists of two phases: installation of an implant into the patient's jaw, and prosthodontic restoration supported by the implant. Either each phase can be performed by a specialist (a maxillofacial surgeon and a prosthodontist), or both phases can be performed by a general practitioner. It is very important that implant placement should be done according to the prosthodontic treatment plan, especially when two specialists treat a patient together[1]. Incorrect placement of implants can make the prosthodontic restoration procedure difficult. Moreover, extremely misplaced implant fixtures might make fabrication of prosthesis impossible and removal might be considered in such cases.[2]

There are many reasons for the placement of implant fixtures at inadequate positions. For example, if a noticeable insufficiency of alveolar bone on the planned area is detected during the course of surgery, the clinician might decide to place implant fixtures on the areas where sufficient bone exists to

achieve stability of the implants rather than at the originally planned location. In short, precise placement of implants is directly dependent on the amount of quality bone in a desirable implant site, as discussed by Graver (1995)[3]. For anterior maxilla rehabilitation, esthetic implant restoration sometimes requires improper implant selection or mispositioning of dental implants (Buser et al, 2004)[4] An angulated abutment is the outcome of the prosthodontic solution. In addition to these issues, dentists face many other problems and as they cannot solve all of them, they are typically required to weigh different suboptimal outcomes and accept the trade-offs.

Although many researchers have noted how restorative procedures can be challenging with undesirable placement, there are few published studies on this issue. Most studies to identify important factors for better prediction of implant prognosis were performed with logistic regression methods or other traditional statistics tools.[5,6] Because the tools used have difficulties in finding predictors with consensus and high accuracy, a new approach should

be applied. The machine learning method, one of the non-traditional statistical tools with better accuracy, utilizes learning algorithms to select the subsets of features with highest classification accuracy by evaluating every set. This new method can overcome the most challenging problem of traditional tools in dental studies – the requirement for sufficient data volume.

The machine learning method is defined as science and technology for self-improving systems based on experienced data and a self-learning algorithm.[7] In this study, decision tree model and support vector machine for the analysis among various methods. Many researchers in medical science are currently applying these machine learning methods such as diagnosing Alzheimer's disease[8] and proving cost-effectiveness in the lung cancer management.[9] However, there are few researches have applied these methods in dental science.

The purpose of this study was to use machine learning methods to determine the most critical factors determining success during surgery or leading to

complications following implantation.

Materials and Methods

Edentulous patients who had undergone dental implant surgeries at Seoul National University Bundang Hospital from June 2004 to October 2005 were enrolled in this study. Subjects included in the analysis were partially edentulous patients who wanted their consecutively missing teeth to be restored by implants, and refused to pay the additional cost for an implant surgical stent. To control for differences between individuals, the included subjects had well-controlled hypertension or diabetes. Smokers and patients with any other systemic disease that was likely to compromise implant survival were excluded[10]. This study was approved by the Institutional Review Board on Human Subjects of Seoul National University Bundang Hospital (IRB No. B-0602-030-016).

After consulting with a prosthodontist about implant location, all operations included in this study were performed by one maxillofacial surgeon with the same surgical protocol. The surgeon placed 667 implants in the mouths of 198

patients according to the anatomic guide structures. Two dental implant systems (Osstem®, Osstem Co., Busan, Korea, and Implantium®, Dentium Co., Yongin, Korea) were used. All subsequent prosthodontic procedures were similarly performed by one prosthodontist. The problems that were confronted during the prosthodontic procedure were assessed and the final prostheses were evaluated by a prosthodontist. At 1 year after prosthodontic restoration the prosthodontist evaluated the implant's location, features, and biomechanical aspects according to the outcome.

The prosthodontic evaluations were categorized into cases according to the chart record. If one patient had several implants, more than one case could exist. We processed the descriptive evaluations into several features designated in binary form for the analysis. During this process, some cases that lacked sufficient information for evaluation were excluded. Therefore, a total of 53 patients and 59 cases were analyzed, and a new method of analysis, the machine learning method was applied because of this paucity of data.

The features consisted of explanatory variables and output variables. The explanatory variables were divided into controllable variables that could be managed by the dentist and host variables (Table 1). There were two kinds of output variables: the first was the success of the implant, evaluated as whether the fixture was osseointegrated or not, and the second was complications of the implant, evaluated as any discomfort or defect despite adequate function with osseointegration (Table 2).

In this study, the machine learning method was selected for analysis. This term was first used in the literature by Samuel (1959), who proposed a learning game through alternating features and weighted values[11]. Thereafter, the machine learning method integrated with computation theory was studied as a new research area in the 1980s. After the 1990s, data mining and the Internet industry promoted machine learning methods as a valuable method in many fields.[12] Document classification, information searching, and various other areas utilize machine learning methods.[13,14]

Because of the binomial data properties, we selected a decision tree model among many available machine learning methods. A decision tree is appropriate for discovering patterns from binomial data with a learning binomial function.[15] The decision tree is often used for classification and prediction, and consists of a root node in the top, internal nodes for grouping criteria, links for nodes, and leaves as the final classification using a recursive partitioning method. Many researchers in medical science are currently applying the decision tree model in diverse fields. Gambhir et al. (1996) reported that positron emission tomography (PET) shows potential cost-effectiveness in the management of non-small cell lung carcinoma through a decision tree model.[16] Yoshio et al. (2013) utilized a machine learning-based decision tree model to classify oral malodor from oral microbiota.[17]

After the decision tree model, we applied a support vector machine to find sets of factors important for implant success. The support vector machine is a supervised learning method used to determine the decision surface with the

best classification of data.[18] This method showed at least equal or better performance to that of other classification methods such as Bayesian classifier or artificial neural network.[19] Support vector machines are widely used in many research areas including character recognition[20], speaker identification[21], document searching[22], and image recognition.[23]

Researchers in the field of medical science use support vector machines in various research areas, such as diagnosing Alzheimer's disease through SPECT image classification with support vector machine[24], discriminating breast cancer patients from a control group based on nucleosides in urine samples,[25] and prognosis of drugs for heart failure patients.[26] However, support vector machines have been rarely used in dental science.

For the decision tree model analysis, learning and classification of the factors affecting success and complication were accomplished using Weka (Waikato Environment for Knowledge Analysis, 3.6.11 ver.)-Java based machine learning software. Linear function was used for classification by the

support vector machine. The evaluation of support vector machine classification by machine learning was carried out by leave-one-out-cross-validation (LOOCV). This method classified one sample with machine learning that was trained using the other 58 samples. Using a confusion matrix, the accuracy, defined as true positive and negative over the whole sample, was calculated.

Table 1. Explanatory variables

Variable classification	Variables	Description
Host variables	Site of placement (Mx, Mn, or Both)	Place of implant in jaws Mandible, Maxilla, or Both
	Site of placement (Ant, Post, or Both)	Place of implant in one side of jaw. Subcategory of above variable
	Posterior Site of placement (Primary molar, Molar, or Primary molar and Molar)	Place of implant in posterior site. Subcategory of above variable
	Bone sufficiency (Adequate or Inadequate)	Degree of bone sufficiency Adequate if bone width is larger than fixture and bone height is greater than 4 mm

	Soft tissue problem (Yes or No)	Whether soft tissue has any problem before placement
	Bone Graft (Yes or No)	Whether bone graft was taken or not
	Bone Graft Resorption (Yes or No)	Whether resorption occurs after bone graft
Controllable variables	Immediate Implantation (Yes or No)	Whether implant is placed immediately after tooth extraction
	Implant insertion depth (Adequate or Inadequate)	Inadequate if there was less than 5 mm between the implant top and the functional cusp tip of the occluding tooth.
	Bucco-lingual angulation (Adequate or Inadequate)	Inadequate when the screw hole of the straight, not angulated, abutment appeared on the buccal or lingual surface of the implant-supported crown
	Mesio-distal position for restoration (Adequate or Inadequate)	Inadequate when the distance between two implants was less than 3 mm or the distance between the implant and the adjacent tooth was less than 1.5 mm.
	Implant length (Adequate or Inadequate)	Inadequate when the length of implant was shorter than 7 mm[27]
	Crown-root ratio (Adequate or Inadequate)	Inadequate if the ratio was less than 1:1.5[28]

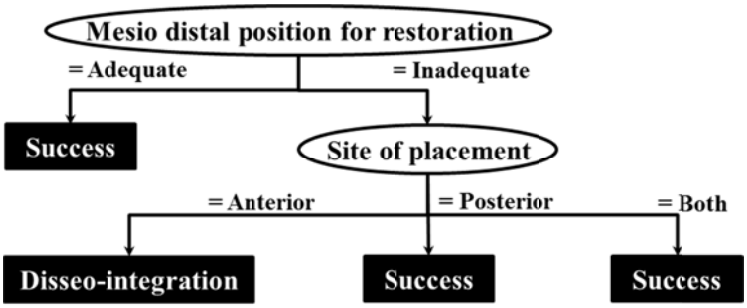
Table 2. Output variables

Variables	Classification	Descriptions
Result	Success	Implant functions well
	Osseo-disintegration	Implant placement fails with osseo-disintegration
	Failure for other reasons	Implant placement fails for other reasons
Complication	None	Implant functions without complication
	Thread/Fixture exposure	Implant functions with thread/fixture exposure
	Screw loosening	Implant functions with screw loosening
	Loading Problem	Implant functions with inappropriate loading on longitudinal axis of implant
	Others	Other complications

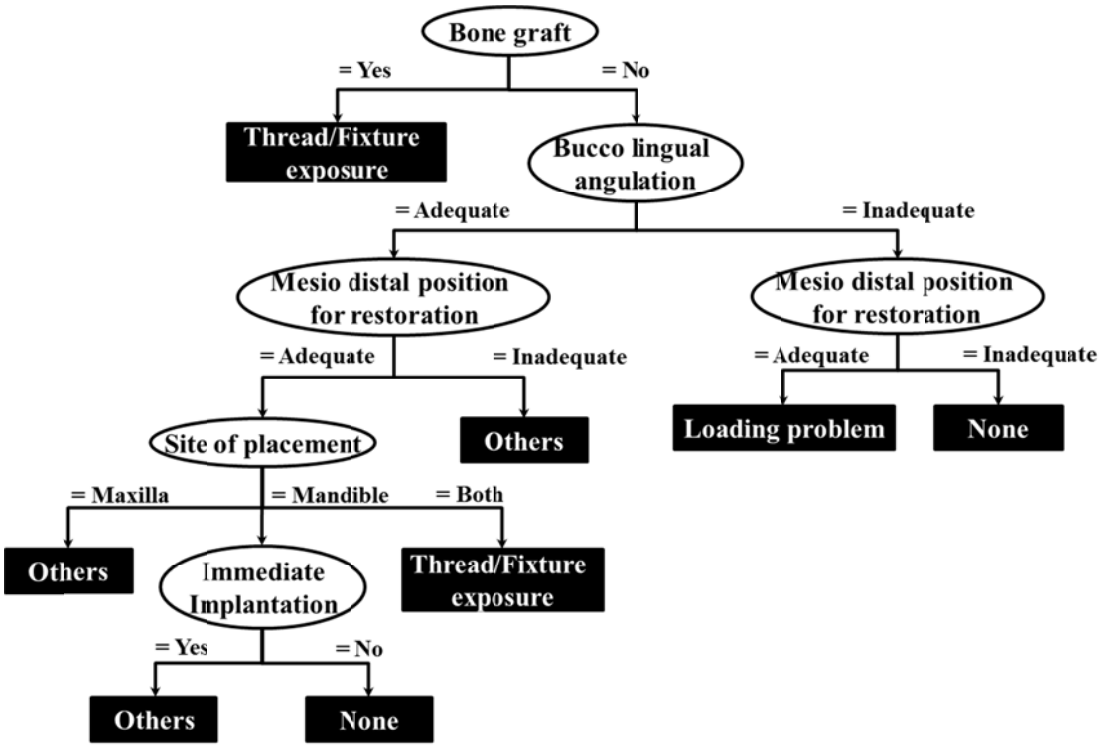
Results

First, both the decision tree model and support vector machine clearly identified ‘mesio-distal position’ as the most important factor during implant treatment. Both complication and success of implant were associated with this factor in the decision tree model and most sets of the support vector machine also included this factor.

The decision tree model showed that the implant functions successfully without disintegration when placed appropriately in the mesio-distal position. Even when this condition is bad, there is no problem if the placement was not in the anterior part of jaw. According to features of the decision tree model, the mesio-distal position variables potentially affected the success of the implant to greater extent because they were located in the root of the tree (Fig. 1, Accuracy = 0.93).



Regarding complications, noticeable thread exposure appeared when the implant was placed with the bone graft. Thread/fixture exposure occurred even when the implants were placed with the appropriate bucco-lingual angulation and mesio-distal position in the maxilla and mandible. This result indicated that there was thread exposure even with adequate bucco-lingual angulation of the implant axis. In addition, loading problems occurred if the implant was placed without bone graft, inappropriate bucco-lingual angulation, and appropriate mesio-distal position. This loading problem led to non-axial loading on the implant (Fig. 2, Accuracy = 0.64).



Support vector machine with leave-one-out-cross-validation (LOOCV) showed outstanding performance in linear kernel function (Tables 3 and 4). In the success measure, two sets with only four features was sufficient to classify the result of the implant with high accuracy (0.95). One of the sets consisted of the following features: site of placement-maxilla or mandible; site of placement-anterior, posterior, or both; posterior site of placement; mesio-distal position for restoration. The other set included the following: site of

placement-anterior, posterior or both; implant insertion depth; bucco lingual angulation; mesio distal position for restoration. Interestingly, both of the sets had one common feature, mesio distal position for restoration. As Bryant (1998) found, most sets showed that the site of placement, whether it is on the maxilla or mandible, was important.[29]

Regarding complication problems of implants, the support vector machine indicated that six factors were important in order to predict the prognosis with the best accuracy (0.746). Two sets commonly included the following five factors: site of placement-anterior, posterior or both; bone graft; bone resorption; bucco lingual angulation; mesio distal position for restoration. The other factors in these two sets were immediate implantation and implant length.

Table 3. Support Vector Machine with LOOCV – Success of implant (top 5 results)

Factors	Accuracy
Site of placement (Mx, Mn, or Both) Site of placement (Ant, Post, or Both) Posterior Site of placement (Prim. Molar, Molar, or Both) Mesio distal position for restoration	0.949152542
Site of placement (Ant, Post, or Both) Implant insertion depth Bucco lingual angulation Mesio distal position for restoration	0.949152542
Site of placement (Mx, Mn, or Both) Site of placement (Ant, Post, or Both) Posterior Site of placement (Prim. Molar, Molar, or Both) Bone sufficiency Mesio distal position for restoration	0.949152542
Site of placement (Mx, Mn, or Both) Site of placement (Ant, Post, or Both) Posterior Site of placement (Prim.Molar, Molar, or Both) Soft tissue problem Mesio distal position for restoration	0.949152542
Site of placement (Mx, Mn, or Both) Site of placement (Ant, Post, or Both) Posterior Site of placement (Prim.Molar, Molar, or Both) Mesio distal position for restoration Crown root ratio	0.949152542

Table 4. Support Vector Machine with LOOCV – Complications of implant (top 5 results)

Factors	Accuracy
Site of placement (Ant, Post, or Both) Bone Graft (Yes or No) Bone Graft Resorption (Yes or No) Immediate Implantation (Yes or No) Bucco lingual angulation Mesio distal position for restoration	0.745762712
Site of placement (Ant, Post, or Both) Bone Graft (Yes or No) Bone Graft Resorption (Yes or No) Bucco lingual angulation Mesio distal position for restoration Implant length	0.745762712
Site of placement (Ant, Post, or Both) Bone Graft (Yes or No) Bone Graft Resorption (Yes or No) Immediate Implantation (Yes or No) Bucco lingual angulation Mesio distal position for restoration Implant length	0.745762712
Site of placement (Ant, Post, or Both) Bone Graft (Yes or No) Bucco lingual angulation Mesio distal position for restoration	0.728813559
Site of placement (Ant, Post, or Both)	0.728813559

Bone Graft (Yes or No)
Bone Graft Resorption (Yes or No)
Bucco lingual angulation
Mesio distal position for restoration

Discussion

Many practitioners have realized how agonizing it is to encounter unexpected situations during fixture placement. We know also how important it is to reach consensus between surgical operation and biomechanical prosthetic rehabilitation. Knowledge of which factor(s) should be primarily considered during the operation would be very valuable for functional rehabilitation.

Several factors have been proposed by other researchers, including quality and quantity of bone, history of trauma to the region, proximity of important structures (sinus, IAN), need for bone grafting, degree of arterial blood supply, and rate of tissue healing.[30] For implant fixture, a wider diameter and long length are known to be important factors for the success of the implant. [31, 32] The shape of dental implants has been one of the most contested aspects and may have an effect on implant biomechanics.[33]

In conclusion, we found that adequate mesio-distal positioning of the

implant significantly affected the prognosis. Thus, site of placement was the most critical feature in our study, as indicated by other research. The small sample size demonstrated the strength of the machine learning method. However, traditional statistical tools should be applied with large samples to verify our conclusion.

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요약

1. 연구목적

본 고에서는 임플란트를 식립할 때 고려되는 다양한 요소 중에서 성공 및 합병증에 영향을 미치는 중요 요소를 기계학습방법(machine learning method)를 이용하여 결정하는 것을 목적으로 한다. 이를 이용하여 임플란트 식립의 예후를 예측할 수 있는 요소를 찾아낸다.

2. 연구대상 및 방법

본 고는 서울대학교 분당 병원에서 2004년 10월부터 2005년 사이의 차트를 데이터로 이용하였다. 보철전문의와의 논의 후에 구강악안면 외과의가 임플란트를 식립하였다. 그 후에, 보철전문의는 생역학적 관점에서 임플란트의 식립위치와 다른 특징들을 평가하였다.

임플란트 수술시에 고려되는 요소들을 분석하기 위하여 decision tree model 과 support vector machine이 이용되었다. Machine learning method를 이용하여 찾아낸 중요 요소들은 decistion tree 또는 요소의 집합들로 표현된다.

3. 결론

임플란트는 근원심적 위치와 협설측적 경사도가 적절하고 악골내에서 후방에 식립될 때 골유착실패 없이 성공적으로 기능하는 것으로 나타났다.

임플란트의 축에 평행하지 않게 교합력이 가해지는 합병증은 골이식을 하지 않은 경우이고 협설측 경사가 적절하였지만, 근원심 위치가 부적절한 경우에 주로 나타났다.

임플란트의 식립 성공은 근원심 위치가 중요한 요소였으며 합병증의 경우 또한 마찬가지이다.

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주요어 : 치과 임플란트, 임플란트 예후, machine learning

method, decision tree model, support vector machine

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