Treatment Algorithm for the Resorption of Calcific Tendinitis Using Extracorporeal Shockwave Therapy

A Data Mining Study

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Background: Although evidence indicates that extracorporeal shockwave therapy (ESWT) is effective in treating calcifying shoulder tendinitis, incomplete resorption and dissatisfactory results are still reported in many cases. Data mining techniques have been applied in health care in the past decade to predict outcomes of disease and treatment.

Purpose: To identify the ideal data mining technique for the prediction of ESWT-induced shoulder calcification resorption and the most accurate algorithm for use in the clinical setting.

Study Design: Case-control study.

Methods: Patients with painful calcified shoulder tendinitis treated by ESWT were enrolled. Seven clinical factors related to shoulder calcification were adopted as the input attributes: sex, age, side affected, symptom duration, pretreatment Constant-Murley score, and calcification size and type. The 5 data mining techniques assessed were multilayer perceptron (neural network), naïve Bayes, sequential minimal optimization, logistic regression, and the J48 decision tree classifier.

Results: A total of 248 patients with calcified shoulder tendinitis were enrolled in this study. Shorter symptom duration yielded the highest gain ratio (0.374), followed by smaller calcification size (0.336) and calcification type (0.253). With the J48 decision tree method, the accuracy of 3 input attributes was 89.5% by 10-fold cross-validation, indicating satisfactory accuracy. A treatment algorithm using the J48 decision tree indicated that a symptom duration of $\leq$10 months was the most positive indicator of calcification resorption, followed by a calcification size of $\leq$10.82 mm.

Conclusion: The J48 decision tree method demonstrated the highest precision and accuracy in the prediction of shoulder calcification resorption by ESWT. A symptom duration of $\leq$10 months or calcification size of $\leq$10.82 mm represented the clinical scenarios most likely to show resorption after ESWT.

Keywords: extracorporeal shockwave therapy; shoulder; calcific tendinitis; data mining; J48 decision tree

Calcific tendinitis of the shoulder is a common degenerative disorder that affects 2.5% to 7.5% of shoulders in the population.[19] The pathomechanism remains controversial, but the circumscribed tissue hypoxia and active cell-mediated processes are generally accepted.[20] Strong evidence indicates that extracorporeal shockwave therapy (ESWT) is effective in treating calcific tendinitis of the shoulder because of its angiogenesis property and anti-inflammation effect, especially in its focused form.[13] Many researchers have reported satisfactory outcomes of ESWT in treating shoulder calcific tendinitis, in both randomized controlled trials and systematic reviews.[5,7,23,24] Nevertheless, incomplete resorption (ICR) and dissatisfactory results have been reported in approximately 44% and 34% of cases, respectively.[3] Negative prognostic factors have been identified, including Gartner and Heyer type 1 calcification,[4] duration of symptoms $>$11 months, and

The Orthopaedic Journal of Sports Medicine, 12(3), 23259671241231609
DOI: 10.1177/23259671241231609

size >15 mm. However, an advanced treatment algorithm to assist decision-making has not been reported to date.

Data mining is a promising technique that has been applied in health care for decades in the investigation of the properties of clinical data sets and to predict the outcomes of disease and treatment.[8,16] There are 2 objectives of data mining techniques: (1) to analyze the attribute importance for databases and (2) to obtain predictive models by data mining for forecasting.[6] Therefore, integration of data mining presents advantages in decision-making capabilities that are beneficial in precision medicine. These techniques have been reported to be beneficial in cardiology,[12] mental health,[1] lung cancer,[11] and skin disease,[22] to name a few areas. To date, there are few reports regarding the application of data mining techniques in the analysis and prediction of treatment outcomes of ESWT, with the exception of plantar fasciitis.[25,26]

The purpose of the present study was to identify the ideal data mining technique for the analysis and prediction of treatment outcomes after ESWT. We focused on an objective indicator of clinical outcomes—ESWT-induced shoulder calcification resorption—rather than subjective patient-reported outcome measures. We also aimed to establish a treatment algorithm for the application of ESWT in the clinical setting.

METHODS

Participants

Institutional review board approval was obtained for the study protocol. From January 1998 to December 2020, patients with a painful shoulder due to calcific tendinitis in whom >3 months of oral medication and physical therapy failed and who were treated using an electrohydraulic mode extracorporeal shockwave device were enrolled. Imaging diagnoses were initially made from plain-film anteroposterior and Y-view radiographs, followed by either shoulder sonography or magnetic resonance imaging to confirm the diagnosis and to exclude other common shoulder lesions such as glenohumeral arthritis, rotator cuff tear, infection, or malignancy. Conditions that were contraindicated for ESWT included malignancy, acute or chronic infection, and coagulopathy. In addition, affected shoulders with fractures or calcific tendinitis coexistent with a rotator cuff tear were excluded. A total of 248 patients with calcific tendinitis of the shoulder met the inclusion criteria for this study.

ESWT Treatment Protocol

Patients were asked to discontinue current treatments, including nonsteroidal anti-inflammatory drugs and aspirin, for 2 weeks prior to ESWT. The patients were placed in either the supine or beach-chair position during the process of treatment. The shockwave was of an electrohydraulic mode delivered using either OssaTron (High Medical Technology; now SANUWAVE) or Orthospec equipment (Medispec). A total of 3000 impulses of the shockwave at 16 to 18 kV (0.28-0.32 mJ/mm^2 energy flux density) or Orthospec level 7 (0.32 mJ/mm^2) were applied to the affected shoulder under ultrasound guidance and in line with the point of tenderness. If symptoms persisted, a second ESWT was performed 3 months later. One year after ESWT was designated the endpoint of treatment.

Clinical Outcome Evaluation

The clinical outcomes evaluated were calcification resorption (complete or incomplete) on plain-film anteroposterior and Y-view radiographs at 1-year follow-up, Constant-Murley score, and patient satisfaction (reported as being complaint-free, significantly better, slightly better, or unchanged). Participants with complete calcification resorption were allocated to the complete resorption (CR) group, while the remainder were assigned to the ICR group.

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Final revision submitted August 15, 2023; accepted August 23, 2023.

One or more of the authors has declared the following potential conflict of interest or source of funding: Funding was received from the National Science and Technology Council in Taiwan (MOST 107-2314-B-182A-032 and NSTC 112-2221-E-037-004-MY3) and the Kaohsiung Medical University (grant No. KMU-DK(A)113015). AOSSM checks author disclosures against the Open Payments Database (OPD). AOSSM has not conducted an independent investigation on the OPD and disclaims any liability or responsibility relating thereto.

Ethical approval for this study was obtained from Chang Gung Medical Foundation (ref No. 202200637B0).

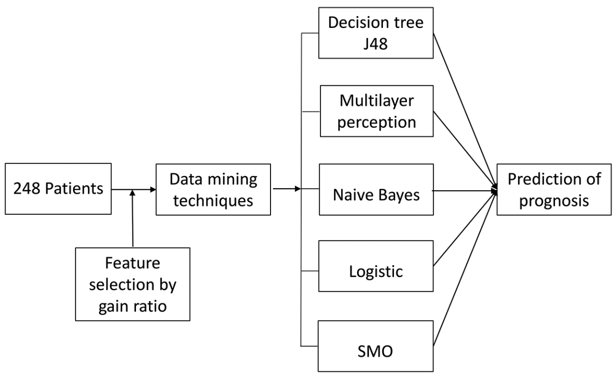


Figure 1. Flowchart showing study procedure. SMO, sequential minimal optimization.

Data Mining Techniques

The output attribute was defined as calcification appearance (ICR or CR). Seven common clinical factors related to shoulder calcification were adopted as the input attributes for analysis. The attributes were divided into radiographic factors (calcification size and calcification type at 1-year follow-up) and clinical factors (sex, age, side affected, symptom duration, and pretreatment Constant-Murley score). The Gartner and Heyer[4] classification was used to categorize calcification into 1 of 3 types (Appendix Figure A1, available in the online version of this article).

The 5 candidate data mining methods were (1) multilayer perceptron (neural network), (2) naïve Bayes, (3) sequential minimal optimization (SMO) algorithm (for training a support vector machine classifier), (4) logistic regression, and (5) J48 decision tree classifier. The data mining techniques were applied via the Weka 3.8.2 program (University of Waikato, New Zealand). We used 10-fold cross-validation and testing data set validation[6] to calculate the predictive accuracy, precision, recall, and F1 score (the weighted mean of the precision and recall values) for each candidate method. For model validation and the creation of the confusion matrix to assess the model's performance, we employed a 20% validation data set extracted from the same data set.

Feature selection is of great importance in the field of data mining. The high-dimension data render building a predictive model using classification methods difficult. To minimize the confounding effects of the inputs, the gain ratio[10] was calculated to determine the strength of each input attribute. The input attributes were progressively tapered off in successive rounds from 6 to 3 to reduce the bias toward multivalued attributes, with input attributes with the lowest gain ratios removed in sequence. The ideal method will have the highest predictive precision calculated from the fewest input attributes from which a feasible clinical algorithm can be developed. The overall procedure of this study is shown in Figure 1.

Multilayer Perceptron. The multilayer perceptron as a form of neural networks represents a fundamental and easily understandable model that has a variety of different and creative applications.[14] The multilayer perceptron may be implemented using a backpropagation algorithm.[17] The desired output vectors for every case as a target function are given in the following equation: $\mathcal{L} = -\sum_{t=1}^{N}\sum_{k=1}^{K} y_{tk} \times \log(\hat{y}_{tk})$, where y_{tk} is the actual state label, $y_{tk} \in \{0, 1\}$, $\sum_{k=1}^{K} y_{tk} = 1$, and $\hat{y}_{tk}$ is its estimator.

Naïve Bayes Classifier. Naïve Bayes classifiers are a collection of classification algorithms based on Bayes law that assume the conditional independence of features.[6] The naïve assumption is the probability of "yes" for ICR being represented on the radiographs while independent of the probability of "no."

Sequential Minimal Optimization. Vladimir Vapnik[21] invented support vector machines in 1979, and these machines have empirically been shown to give good generalization performance on a wide variety of problems. SMO breaks this large quadratic programming problem into a series of smallest possible quadratic programming problems,[15] whose ultimate goal is to identify all of the nonzero Lagrange multipliers and discard all of the zero Lagrange multipliers.

Logistic Regression. Logistic regression is derived from linear regression and is a basic binary linear classifier whose goal is to find a straight line that can clearly separate and classify all data.[6] Logistic regression actual explains the meaning of a probability. A set of parameters are obtained through training a function, so different weights and biases will result in different functions.

J48 Decision Tree. The J48 decision tree method is a flowchart-like decision tree structure, one of the data mining techniques used for classification. It is a supervised method that is generally used to build a predictive model, and it can analyze multidimensional data into simple and easy-to-understand rules. The advantages of the J48 decision tree method are that it does not require any domain knowledge, and it is suitable for data-driven exploratory knowledge discovery in databases.[6,14,17]

Statistical Analysis

Statistical analysis was conducted using SPSS for Windows (Version 22.0; IBM). Comparisons between the CR and ICR groups were conducted with the chi-square test for categorical variables (patient sex, side affected, calcification type, and patient satisfaction) and the Mann-Whitney *U* test for continuous variables (age, symptom duration, Constant-Murley score, and calcification size). Statistical significance was set at $P < .05$.

RESULTS

Of the 248 included shoulders, 141 achieved CR of calcification 1 year after ESWT, leaving 107 shoulders in the ICR group. The overall rate of calcification resorption was 57%.[3] The participant characteristics in terms of input and output attributes are presented in Table 1. The information presented in Table 2 demonstrates significant differences between the CR and ICR groups; symptom duration, calcification size, and calcification type were

TABLE 1
Input and Output Attributes of the Study Participants[a]

Attribute	Value
Input attribute	
Sex	
Female	180 (73)
Male	68 (27)
Age, y	52.99 ± 8.714 (31-82)
Side affected	
Right	152 (61)
Left	96 (39)
Symptom duration, mo	19.113 ± 22.617 (6-240)
Constant-Murley score before ESWT	52.895 ± 9.477 (24-73)
Calcification size, mm	17.221 ± 9.442 (2.5-51.2)
Calcification type	
Type 1	83 (33)
Type 2	109 (44)
Type 3	56 (23)
Output attribute	
Appearance	
Yes, incomplete resorption	107 (43)
No, complete resorption	141 (57)

[a]Data are reported as mean ± SD (range) or n (%).

the significant pre-ESWT clinical factors. The CR group had higher patient-reported satisfaction and Constant-Murley scores than the ICR group, indicating that CR was related to clinical improvement in this study.

Gain Ratios

Symptom duration yielded the highest gain ratio (0.374), followed by calcification size (0.336) and calcification type (0.253), as shown in Figure 2. Thus, the feature with the lowest gain ratio (age) was removed when considering 6 input attributes, and successive features with the lowest gain ratios, as shown in Figure 2, were removed when considering 5, 4, and 3 input attributes.

Results of Cross-Validation Analysis

The results of the 10-fold cross-validation demonstrated that the J48 decision tree method (from 7 input attributes to 3 input attributes) reached the gross highest accuracy, precision, recall, and F1 score as compared with the other 4 methods (Table 3). As can be seen in Table 3, the highest accuracies from 7 input attributes to 3 input attributes were 0.895, 0.879, 0.883, 0.875, and 0.895, respectively, hence showing a satisfactory accuracy using the J48 decision tree method. The results for the validation of the testing data set (20%) and the confusion matrix of the J48 decision tree are provided in Appendix Tables A1 and A2 (available online), respectively.

From Table 3, it can be observed that in the J48 decision tree method, the 3-input attribute model (symptom duration, calcification size, and calcification type) showed a result not inferior to the results of the different input models, at near 90% accuracy. This indicated that these 3 inputs were the determiners that affected calcification resorption by ESWT.

TABLE 2
Comparison of Clinical Attributes Between the CR and ICR Groups[a]

Attribute	CR (n = 141)	ICR (n = 107)	*P* Value
Sex			.125
Female	97 (68.8)	83 (77.6)	
Male	44 (31.2)	24 (22.4)	
Age, y	53.1 ± 9.1 (31-82)	52.8 ± 8.2 (32-74)	.781
Side affected			.677
Right	88 (62.4)	64 (59.8)	
Left	53 (37.6)	43 (40.2)	
Symptom duration, mo	12.1 ± 9.8 (6-48)	28.4 ± 30.2 (6-240)	**<.001**
Constant-Murley score before ESWT	54.8 ± 11.7 (24-73)	53.2 ± 8.2 (37-69)	.162
Calcification size, mm	12.5 ± 6.7 (2.5-34)	23.4 ± 9.0 (5.6-51.2)	**<.001**
Calcification type			**<.001**
Type 1	14 (9.9)	69 (64.5)	
Type 2	86 (61.0)	23 (21.5)	
Type 3	41 (29.1)	15 (14.0)	
Constant-Murley score after ESWT	89.0 ± 16.4 (33-100)	67.9 ± 19.3 (37-100)	**<.001**
Satisfaction rate			**<.001**
Complaint-free	108 (76.6)	23 (21.5)	
Significantly better	10 (7.1)	21 (19.6)	
Slightly better	6 (4.3)	14 (13.1)	
No change	17 (12.1)	49 (45.8)	

[a]Data are reported as mean ± SD (range) or n (%). Boldface *P* values indicate a statistically significant difference between the study groups ($P < .05$). CR, complete resorption; ESWT, extracorporeal shockwave therapy; ICR, incomplete resorption.

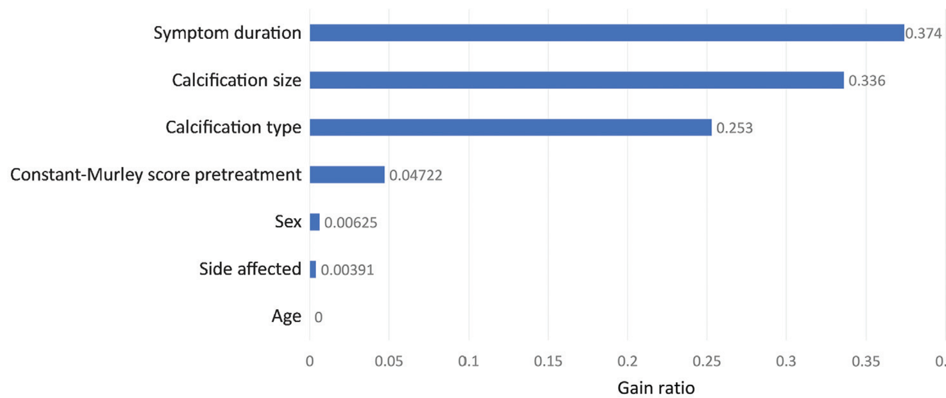


Figure 2. Gain ratios of the 7 input attributes.

TABLE 3
Results of the 10-Fold Cross-Validation Analysis[a]

No. of Input Attributes	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
J48 decision tree				
7	89.5	90.1	91.4	90.7
6	87.9	88.0	90.6	89.3
5	88.3	85.2	93.8	89.3
4	87.5	85.9	91.7	88.7
3	89.5	87.3	93.9	90.5
Multilayer perceptron				
7	85.9	85.9	87.9	87.6
6	85.5	89.4	85.8	87.6
5	84.3	89.4	84.1	86.7
4	84.7	88.7	85.1	86.9
3	85.5	91.5	84.4	87.8
Naïve Bayes classifier				
7	82.2	91.5	80.2	85.5
6	82.7	92.3	80.4	85.9
5	81.9	91.5	79.8	85.3
4	82.3	92.3	79.9	85.7
3	82.3	93.0	79.5	85.7
Logistic regression				
7	86.3	90.1	86.5	88.3
6	85.9	90.8	85.4	88.0
5	86.7	89.4	87.6	88.5
4	86.7	89.4	87.6	88.5
3	86.3	90.1	86.5	88.3
SMO				
7	82.0	88.7	82.3	85.4
6	82.7	88.7	82.4	85.4
5	82.7	88.7	82.4	85.4
4	82.7	88.7	82.4	85.4
3	83.1	89.4	82.5	85.8

[a]SMO, sequential minimal optimization.

Based on the high accuracy and precision of the J48 decision tree method with 3 input attributes, the decision tree was further developed. The J48 decision tree treatment algorithm as shown in Figure 3 showed that a symptom duration of ≤10 months could be the first positive indicator of calcification resorption, as only 1 of 92 shoulders failed to respond to ESWT in this circumstance. The next positive indicator was a calcification size of ≤10.82 mm when the duration of symptoms was >10 months. When the calcification size was ≤10.82 mm, nearly all calcification (33/34 shoulders) was completely resorbed, regardless of type. If the size was >10.82 mm

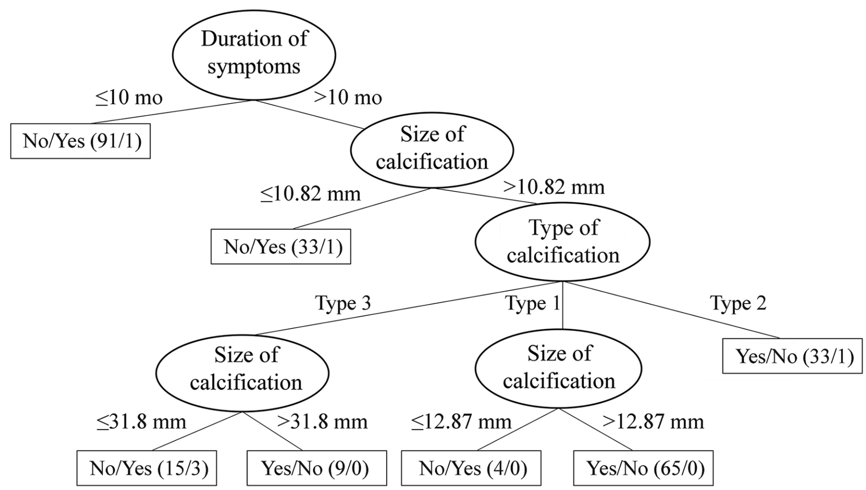


Figure 3. J48 decision tree treatment algorithm for extracorporeal shockwave therapy (ESWT). ''Yes'' and ''no'' responses are the number of shoulders that did or did not show radiographic calcification after ESWT, respectively.

with a duration of symptoms >10 months, most calcification failed to achieve CR after ESWT, with the exception of some cases of type 3 calcification.

DISCUSSION

The principal findings of the present study showed that a popular predictive model with data mining techniques contributed a high prediction precision and accuracy when applied in the prediction of calcification resorption after ESWT. The gain ratio calculations proved that the duration of symptoms, calcification size, and calcification type were the significant input attributes, and the J48 decision tree presented the highest precision and accuracy (Table 3). The J48 decision tree treatment algorithm (Figure 3) can aid in decision-making regarding the application of ESWT in shoulder calcific tendinitis. In patients with symptom duration of ≤10 months and a calcification size of ≤10.82 mm, ESWT achieved near-complete resorption of calcification. To the best of our knowledge, this is the first study of data mining techniques focused on the use of ESWT for the resorption of calcific tendinitis of the shoulder.

ESWT delivers a higher rate of clinical improvement than calcification resorption, with the reported clinical improvement ranging from 85% to 97% and the rate of successful resorption ranging from 71% to 87.9%.[13] Controversy exists regarding the relationship between calcification resorption and clinical improvement. Some researchers have reported that calcium deposition does not correspond with symptom severity.[2,9,18] However, Chou et al[3] reported an 88.1% rate of clinical improvement in their patients with calcification resorption, which was significantly superior to the 54.2% reported in their patients with ICR. Complete removal of the calcic focus may not be necessary for a good outcome, but a reduction in calcific size is believed to be beneficial for symptom improvement. As shown in Table 2, the patients with CR demonstrated superiority in terms of reported satisfaction rate and Constant-Murley score. In the present study, we did not adopt clinical improvement as the output attribute, as a subjective assessment may include bias and may therefore be inappropriate for data mining techniques. Instead, we used the more objective outcome measure of calcification appearance as the output attribute for less assessment bias and lack of placebo effect.

Artificial intelligence has been experienced 2 rises and falls, as early as the 1950s to 1980s. However, deep learning algorithms often require very huge amounts of data when building learning models. Regarding ESWT, previous studies have identified the predictive factors in the treatment of plantar fasciitis,[25,26] but not in shoulder calcific tendinitis. Differing from the use of statistics and statistical models to infer relationships among variables, the predictive models of data mining techniques are designed to offer accurate predictions. The present study revealed that the neural network, naïve Bayes, SMO, logistic regression, and J48 decision tree methods presented high gross percentages (>80%) for accuracy, precision, recall, and F1 score, indicating that these data mining techniques were feasible and reliable for the prediction of the outcome of ESWT for calcific tendinitis. The most significant benefit of these data mining results was the aid to decision-making, providing a clinical algorithm that can be used by the physician regarding the application of ESWT for the treatment of shoulder calcific tendinitis.

In the treatment algorithm created by the J48 decision tree architecture (Figure 3), ESWT induced near-CR of calcification (90/91 [98.9%]) in patients with symptom duration of ≤10 months, regardless of type or size of calcification. This indicated that early ESWT intervention after the calcific stage[20] is crucial, and the first determinant of calcification resorption induced by ESWT. The ideal timing of intervention should be the period around

10 months after symptom onset, rather than the precise time point of the 10th month. Because of the biologic response induced by ESWT,[13] this modality is not recommended for application in cases of acute inflammation and severe pain. The next determinant was calcification size. A calcification size of $\leq$10.82 mm responded well to ESWT, regardless of dense or translucent calcification. For patients with symptoms for $>$10 months with a calcification size of $\leq$10.82 mm, ESWT would be an optimal choice.

Limitations

There are several limitations to the present study. First, the large age variation might have affected the study outcomes. Second, the duration of symptoms relied on patient recall, which may have resulted in recall bias and a decrease in prediction accuracy. Therefore, we suggest that the optimal timing of intervention should be around 10 months after symptom onset, rather than a specific time point within the 10th month. Third, the sample size of 248 patients was relatively small for constructing a comprehensive predictive model using data mining techniques. To strengthen the robustness of our finding, a larger sample size and a validation subset from different data set would be valuable. Fourth, it is important to note that the current method yielded results related to the prediction of calcification resorption rather than patient-reported outcomes, which are relatively subjective and lack scientific objectivity. Developing a predictive model for patient-reported outcomes is the logical next step in our research.

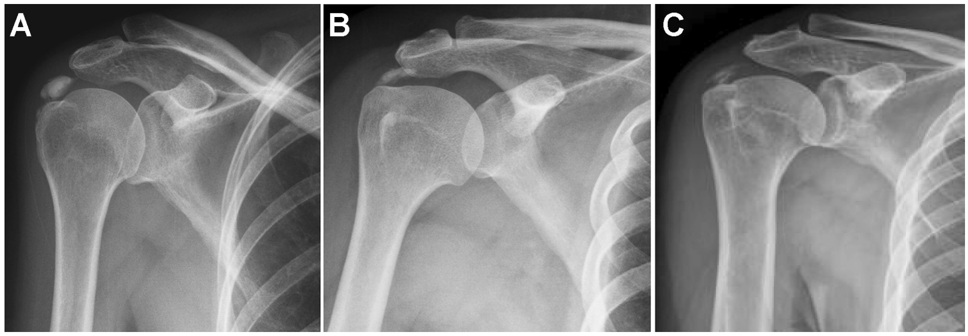
CONCLUSION

In the current study, the J48 decision tree method demonstrated the highest precision and accuracy for predicting shoulder calcification resorption by ESWT. Specifically, a symptom duration of $\leq$10 months or a calcification size of $\leq$10.82 mm represented the clinical scenarios most likely to show resorption after ESWT.

REFERENCES

1. Alonso SG, de la Torre-Diez I, Hamrioui S, et al. Data mining algorithms and techniques in mental health: a systematic review. *J Med Syst*. 2018;42(9):161.
2. Cho NS, Lee BG, Rhee YG. Radiologic course of the calcific deposits in calcific tendinitis of the shoulder: does the initial radiologic aspect affect the final results? *J Shoulder Elbow Surg*. 2010;19(2):267-272.
3. Chou WY, Wang CJ, Wu KT, et al. Prognostic factors for the outcome of extracorporeal shockwave therapy for calcific tendinitis of the shoulder. *Bone Joint J*. 2017;99(12):1643-1650.
4. Gartner J, Heyer A. Calcific tendinitis of the shoulder. In German. *Orthopade*. 1995;24(3):284-302.
5. Gerdesmeyer L, Wagenpfeil S, Haake M, et al. Extracorporeal shock wave therapy for the treatment of chronic calcifying tendonitis of the rotator cuff: a randomized controlled trial. *JAMA*. 2003;290(19):2573-2580.
6. Han J KM, Pei J. *Data Mining: Concepts and Techniques*. 3rd ed. Morgan Kaufmann Publishers; 2011.
7. Hsu CJ, Wang DY, Tseng KF, et al. Extracorporeal shock wave therapy for calcifying tendinitis of the shoulder. *J Shoulder Elbow Surg*. 2008;17(1):55-59.
8. Itani S LF, Fortemps. Specifics of medical data mining for diagnosis aid: a survey. *Expert Syst Appl*. 2019;118:300-314.
9. Jacobs R, Debeer P. Calcifying tendinitis of the rotator cuff: functional outcome after arthroscopic treatment. *Acta Orthop Belg*. 2006;72(3):276-281.
10. Karegowda AG MA, Jayaram MA. Comparative study of attribute selection using gain ratio and correlation based feature selection. *Int J Inf Technol Knowl Manag*. 2010;2(2):271-277.
11. Li D, Li Z, Ding M, et al. Comparative analysis of three data mining techniques in diagnosis of lung cancer. *Eur J Cancer Prev*. 2021;30(1):15-20.
12. Martins B, Ferreira D, Neto C, Abelha A, Machado J. Data mining for cardiovascular disease prediction. *J Med Syst*. 2021;45(1):6.
13. Moya D, Ramon S, Schaden W, et al. The role of extracorporeal shockwave treatment in musculoskeletal disorders. *J Bone Joint Surg Am*. 2018;100(3):251-263.
14. Nikulin V, Huang TH, McLachlan GJ. Classification of high-dimensional microarray data with a two-step procedure via a Wilcoxon criterion and multilayer perceptron. *Int J Comput Intell Appl*. 2012;10(01):1-14.
15. Platt JC. Sequential minimal optimization: a fast algorithm for training support vector machines. Technical Report MSR-TR-98-14. Microsoft; April 1998. Accessed February 8, 2024. https://www.microsoft.com/en-us/research/publication/sequential-minimal-optimization-a-fast-algorithm-for-training-support-vector-machines
16. Ristevski B, Chen M. Big data analytics in medicine and healthcare. *J Integr Bioinform*. 2018;15(3).
17. Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. *Nature*. 1986;323(6088):533-536.
18. Sabeti-Aschraf M, Dorotka R, Goll A, Trieb K. Extracorporeal shock wave therapy in the treatment of calcific tendinitis of the rotator cuff. *Am J Sports Med*. 2005;33(9):1365-1368.
19. Serafini G, Sconfienza LM, Lacelli F, et al. Rotator cuff calcific tendonitis: short-term and 10-year outcomes after two-needle US-guided percutaneous treatment—nonrandomized controlled trial. *Radiology*. 2009;252(1):157-164.
20. Uhthoff HK, Loehr JW. Calcific tendinopathy of the rotator cuff: pathogenesis, diagnosis, and management. *J Am Acad Orthop Surg*. 1997;5(4):183-191.
21. Vapnik V. *Estimation of Dependences Based on Empirical Data*. 1st ed. Springer; 2006.
22. Verma AK, Pal S, Kumar S. Classification of skin disease using ensemble data mining techniques. *Asian Pac J Cancer Prev*. 2019;20(6):1887-1894.
23. Verstraelen FU, In den Kleef NJ, Jansen L, Morrenhof JW. High-energy versus low-energy extracorporeal shock wave therapy for calcifying tendinitis of the shoulder: which is superior? A meta-analysis. *Clin Orthop Relat Res*. 2014;472(9):2816-2825.
24. Wang CJ, Yang KD, Wang FS, Chen HH, Wang JW. Shock wave therapy for calcific tendinitis of the shoulder: a prospective clinical study with two-year follow-up. *Am J Sports Med*. 2003;31(3):425-430.
25. Yin M, Chen N, Huang Q, et al. New and accurate predictive model for the efficacy of extracorporeal shock wave therapy in managing patients with chronic plantar fasciitis. *Arch Phys Med Rehabil*. 2017;98(12):2371-2377.
26. Yin M, Ma J, Xu J, et al. Use of artificial neural networks to identify the predictive factors of extracorporeal shock wave therapy treating patients with chronic plantar fasciitis. *Sci Rep*. 2019;9(1):4207.

APPENDIX



Appendix Figure A1. Gartner and Heyer[4] classification of calcification. (A) Type 1: well circumscribed, dense. (B) Type 2: soft contours/dense or sharp/transparent. (C) Type 3: translucent and cloudy appearance without clear circumscription.

APPENDIX TABLE A1
Results for the Validation of the Testing Data Set (20%)[a]

No. of Input Attributes	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
J48 decision tree				
7	92.0	92.9	92.9	92.9
6	92.0	92.9	92.9	92.9
5	92.0	89.3	96.2	92.6
4	92.0	89.3	96.2	92.6
3	90.0	85.7	96	90.6
Multilayer perceptron				
7	80.0	75.0	87.5	80.8
6	86.0	78.6	95.7	86.3
5	88.0	82.1	95.8	88.4
4	84.0	82.1	88.5	85.2
3	82.0	85.7	82.8	84.2
Naïve Bayes classifier				
7	76.0	85.7	75.0	80.0
6	76.0	85.7	75.0	80.0
5	76.0	85.7	75.0	80.0
4	74.0	85.7	72.7	78.7
3	74.0	85.7	72.7	78.7
Logistic regression				
7	86.0	82.1	92.0	86.8
6	86.0	82.1	92.0	86.8
5	82.0	78.6	88.0	83.0
4	82.0	78.6	88.0	83.0
3	84.0	78.6	91.7	84.6
SMO				
7	80.0	85.7	80.0	82.8
6	80.0	85.7	80.0	82.8
5	76.0	82.1	76.7	79.3
4	78.0	85.7	77.4	81.3
3	78.0	85.7	77.4	81.3

[a]SMO, sequential minimal optimization.

APPENDIX TABLE A2
Confusion Matrix of the J48 Decision Tree Method by Testing Data Set (20%) Validation[a]

	True Classification	
J48 Decision Tree Classification	Yes	No
Yes	21	4
No	1	24

[a]J48 decision tree with 3 input attributes was used.