

Machine Learning vs. Logistic Regression for Classifying Pressure Pain Hypersensitivity Based on Postural Analysis Data in Food Service Workers with Nonspecific Neck/Shoulder Myofascial Pain

Ui-jae Hwang, PT, Ph.D; Gyeong-tae Gwak, PT, Ph.D

Department of Physical Therapy, College of Health Science, Laboratory of KEMA AI Research (KAIR), Yonsei University, Wonju, Republic of Korea

Background Pressure pain hypersensitivity (PPH) is used to measure pain sensitivity in deep tissues, but factors contributing to PPH remain unclear. Abnormal neck and scapula posture are thought to play a role in shoulder pain. Traditional statistical methods like logistic regression have limitations in capturing complex relationships, while machine learning (ML) can model nonlinear relationships effectively.

Purpose The purpose of the present study was to develop, evaluate, and compare the predictive performance of ML models and logistic regression for classifying food service workers (FWs) with and without PPH based on postural analysis data.

Study design Cross sectional study

Methods FWs (n=150) meeting specific criteria were assessed for PPH and underwent postural analysis. ML algorithms (logistic regression, neural network, random forest, gradient boosting, decision tree, and support vector machine) were used for classification. Model performance was evaluated using the area under the curve (AUC), accuracy, recall, precision, and F1 score. Feature importance was assessed.

Results Gradient boosting exhibited the best performance (AUC: 0.867) in classifying PPH, followed by random forest (AUC: 0.822) in the test dataset. Logistic regression performed less effectively (AUC: 0.613). For feature importance analysis, scapular downward rotation ratio, forward head posture, BMI and rounded shoulder angle were the top four important predictors of PPH in gradient boosting model.

Conclusions Gradient boosting, along with identified predictors, offers promise for early intervention and risk assessment tools in addressing musculoskeletal pain in food service workers.

Key words Food service workers; Machine learning; Myofascial pain; Pressure pain hypersensitivity

**J Musculoskelet
Sci Technol**

2023; 7(2): 71-79

Published Online

Dec 31, 2023

pISSN 2635-8573

eISSN 2635-8581



Article History

Received 10 Oct 2023

Revised 30 Oct 2023

(1st)

Accepted 2 Nov 2023

CONTACT

smartkema@yonsei.ac.kr

Ui-jae Hwang,

Department of Physical
Therapy, College of
Health Science,
Laboratory of KEMA AI
Research (KAIR), Yonsei
University, Wonju,
Republic of Korea

This is an Open-Access article distributed under the terms of the Creative Commons Attribution Non-Commercial License (<http://creativecommons.org/licenses/by-nc/4.0>) which permits unrestricted non-commercial use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

Food service workers (FWs), including cooks and restaurant staff, face a heightened risk of musculoskeletal pain due to the physical demands of their jobs, such as serving, food preparation, dishwashing, and cooking.¹⁻⁴ Numerous studies have reported a high prevalence of musculoskeletal pain in this occupational group, with the neck (54.3%) and

shoulders (57.9%) being the most commonly affected body regions.^{5,6}

Myofascial pain (MP) is a leading cause of musculoskeletal discomfort,⁷ and the upper trapezius muscle (UT) is particularly susceptible to MP.^{7,8} Tenderness in the muscles is a common clinical observation in cases of suspected muscular pain.^{9,10} To quantify pain sensitivity in deep tissues, pressure pain sensitivity (PPS) is employed as a

neurophysiological test.¹¹ PPS and tissue tenderness are thought to be measurable through this test because they are believed to decrease test values.¹¹ Although the underlying mechanism of MP remains unidentified, it may involve central sensitization, characterized by the central nervous system's hyperresponsiveness and hyperexcitability.^{12,13} However, the factors that elevate the risk of developing pressure pain hypersensitivity (PPH) in terms of neurophysiological hyperresponsiveness and hyperexcitability are still unclear.

Abnormal neck and scapula posture can also contribute to shoulder pain, as corroborated by previous studies examining factors influencing UT pain associated with MP.¹⁴ In the sagittal plane, forward head posture is characterized by an anterior position along the postural line¹⁵ and may be accompanied by reduced range of motion, pain, muscle stiffness, and spinal degenerative changes. Forward head posture is indicative of shortened UT and levator scapulae muscles, resulting in elevated scapulae. Correcting abnormal alignments is necessary to facilitate optimal motion.^{14,16} Additionally, abnormal scapular alignment has been suggested as a potential cause of UT pain.^{16,17} Such abnormalities include scapular depression, downward rotation, and abduction.¹⁶ A downwardly rotated, depressed, or abducted scapula, often associated with rounded shoulders, leads to lengthening of the UT,^{18,19} resulting in increased tension and reduced pressure pain threshold (PPT) in the UT.¹⁷

Most research on classifying PPH or MP at UT has traditionally used linear or logistic regression as statistical methods to identify key contributing factors, depending on whether the outcomes are continuous or binary.²⁰ However, these methods have limitations when the relationships between the outcome (or logit of the outcome) and the contributing factors are nonlinear. In contrast, machine learning (ML) is gaining prominence for classification models due to its ability to model both highly nonlinear and linear relationships.²¹ It has been recommended for achieving higher accuracy compared to traditional statistical methods.^{20,21}

Therefore, the primary objective of this study is to develop, evaluate, and compare the predictive performance of ML models and logistic regression for classifying FWs with and without PPH based on postural analysis data (forward head posture, rounded shoulder angle, and scapular downward rotation ratio). Additionally, the secondary aim is to identify significant contributing factors that impact PPH and provide insights into a model that can aid in the prevention and management of PPH among FWs by addressing these factors.

METHODS

Participants

Participants for this study were enlisted through a questionnaire to ascertain their experience of neck/shoulder MP as FWs. A total of 163 individuals suffering from neck/shoulder MP were included, selected from a pool of 372 FWs employed at a theme park. The present study was performed from March 2016 to November 2016. A flowchart for recruitment of the participants is shown in Figure 1. Participants were assessed at the work conditioning center in a theme park. The inclusion criteria mandated non-traumatic neck and shoulder pain, a minimum of six months of work experience in food service, neck and shoulder pain persisting for at least three months, and a visual analog scale (VAS) score exceeding 3 points. Exclusion criteria encompassed individuals with shoulder fractures, a previous diagnosis of shoulder instability, a history of shoulder surgery, any systemic diseases, untreated psychiatric conditions, indications of neurological or internal diseases upon examination, hypertension (defined as resting systolic blood pressure exceeding 150 mm Hg or diastolic blood pressure exceeding 90 mm Hg), and pregnancy. Details about the participants' characteristics can be found in Table 1. This research protocol was granted approval by the Yonsei University Mirae Campus Institutional Review Board (certification number: #1041849-201603-BM-005-02). Prior to any assessment, the investigator provided a comprehensive explanation of the entire experimental procedure, and all participants voluntarily gave their informed consent.

Outcome measurements

1) Pressure pain sensitivity (PPS)

To gauge PPS, we employed a pressure algometer (FPK 60, Wagner Instruments, Inc., Greenwich, CT, USA). This device featured a rubber-tipped probe with a 1 cm diameter, connected to a strain gauge that displayed measurements in kg/cm². PPS assessment was conducted with the participant seated upright, targeting a standardized location on the upper trapezius (UT) muscle, precisely between the C7 vertebra and the acromion process. It's worth noting that inter-rater reliability was high, with an intraclass correlation coefficient of 0.91.^{22,23} In our study, we defined PPS as the minimum pressure level at which the sensation of pressure transitioned into slight pain or discomfort, consistent with previous research.²²⁻²⁴ To ensure accuracy, we conducted three trials for each participant and calculated the mean value for the primary analyses. We implemented a one-

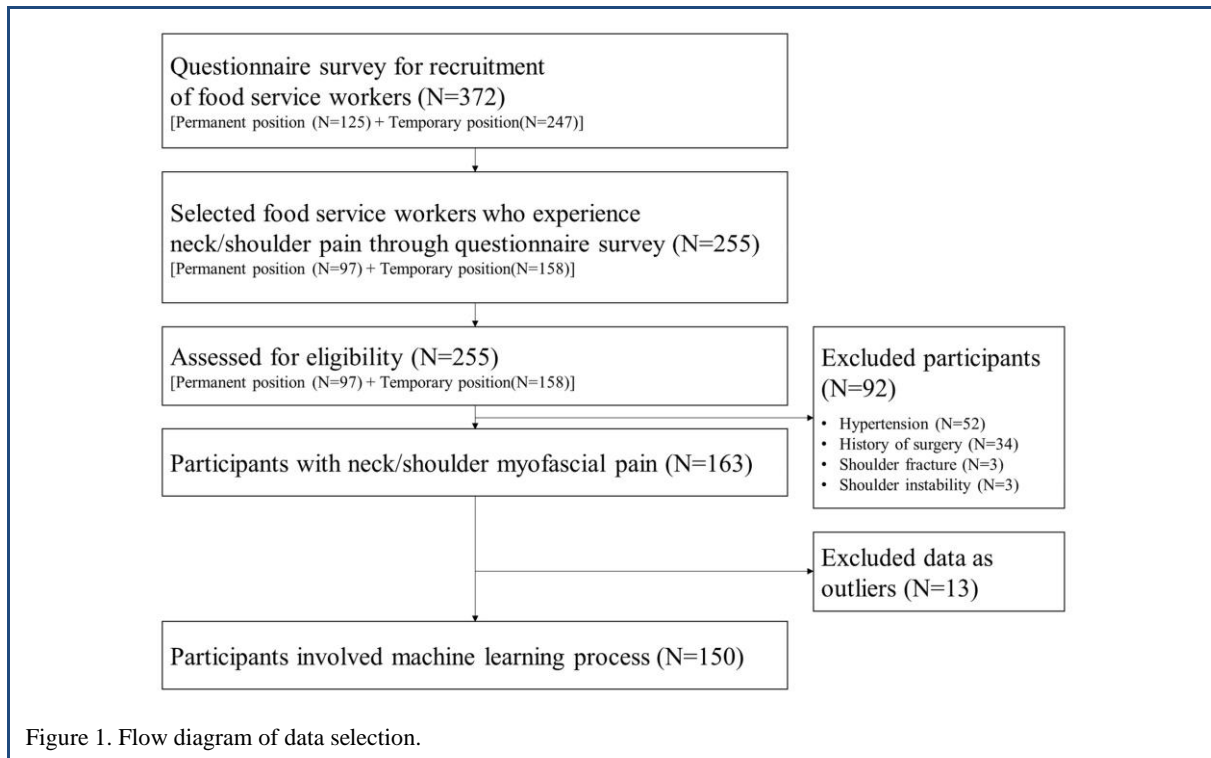


Table 1. Mean±standard deviation of baseline characteristics in FWs with and without PPH

Variables	Without pressure pain hypersensitivity (N=64)	With pressure pain hypersensitivity (N=86)	<i>p</i>
Sex	16/48	44/42	-
Age	26.45±6.7	29.09±8.9	0.039
BMI	21.71±2.89	22.47±2.63	0.097
Pain intensity	50.88±19.10	51.68±20.00	0.80
Pain side	33/31	43/43	-
Rounded shoulder angle	36.31±6.63	37.22±5.11	0.363
Forward head posture	56.65±12.17	54.54±9.68	0.255
Scapular downward rotation ratio	0.9±0.15	0.86±0.14	0.098

minute resting interval between each recording to avoid any potential bias. Both the participant and the examiner were kept unaware of the force readings throughout the assessment process. Additionally, we used a standard metronome to control the rate at which pressure was applied.

In terms of PPH classification, men with pressure pain sensitivity measuring less than 2.9 kg/cm² in the UT and women with pressure pain sensitivity measuring less than 2.0 kg/cm² in the UT were categorized as having PPH.^{4,25}

2) Postural analysis

We used a camera (EOS 100D, Canon, Japan) to measure forward head posture, rounded shoulder angle, and scapular downward rotation ratio in the sagittal, transverse, and frontal planes. To facilitate this measurement, retro-reflec-

tive markers were strategically placed on specific anatomical landmarks, including the scapular acromions, the seventh cervical vertebra (C7), medial roots of the scapula, and the inferior angles of the scapula.^{26,27} Photographs were taken in the lateral, transverse and posterior views while subjects maintained a frontal gaze in a standing position. The camera, positioned on a tripod, was situated 140 cm from the floor and 250 cm away from the subjects, aligned perpendicular to the camera in the lateral and posterior photographs. Transverse photographs were captured with the camera at a height above 60 cm and below 10 cm from the subject's head.

For posture analysis, we utilized ImageJ software (National Institutes of Health, Bethesda, MD, USA) to conduct kinematic assessments of the photographs. Specifically, we

quantified forward head posture by measuring the crani-oververtebral angle, which is the angle between the horizontal line passing through C7 and a line extending from the tragus of the ear to C7 (Figure 2). The rounded shoulder angle was determined by calculating the angle (θ) between two lines: one extending from a horizontal line in the medial roots of the scapula to the acromion, and the other from the root of the scapula to the acromion. To define the rounded shoulder angle, we subtracted θ from 90 degrees (Figure 2).²⁶ Finally, the scapular downward rotation ratio was quantified as the ratio between two lines: a vertical line drawn from the center to the root of the scapula and another vertical line drawn from the center to the scapular inferior angle (Figure 2).²⁶

Machine learning modeling

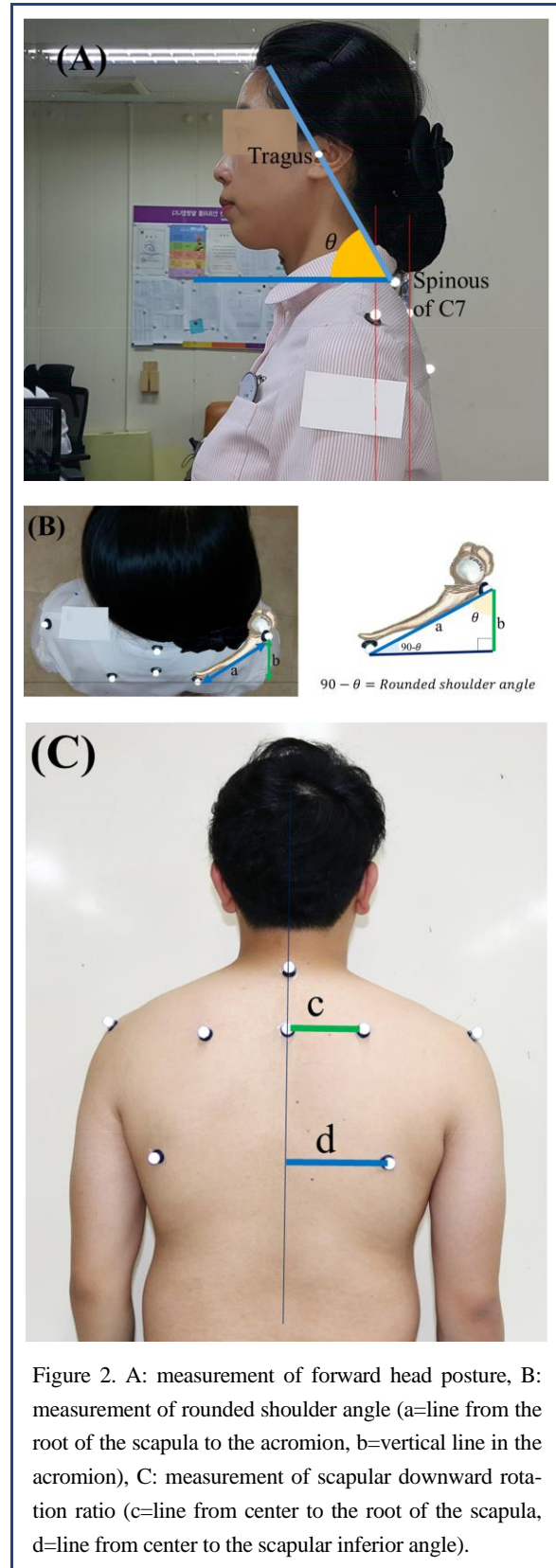
We conducted our machine learning (ML) analysis using Orange data mining software (Version 3.3.0, developed in Ljubljana, Slovenia) in conjunction with Python (Version 3.6.15, developed by the Python Software Foundation). In addition, we performed independent *t*-test to compare baseline characteristics between FWs with and without PPH.

1) Data pre-processing and handling missing data

Our study incorporated six predictors, including five numeric variables (age, BMI, forward head posture, rounded shoulder angle, and scapular downward rotation ratio) and one categorical variable (sex). The target variable was transformed into a dichotomous variable, distinguishing between those with and without PPH. To address missing data, we performed exploratory data analysis and eliminated instances with unknown values. We carefully examined the distribution of each variable using various visualization methods, including boxplots, scatterplots, and linear projections. Outliers were eliminated because of potentially impact the model's accuracy. We employed a local outlier factor (with parameters set at a contamination rate of 10%, 20 neighbors, and the Euclidean metric) to detect and remove outliers.

2) Machine learning algorithms

The complete dataset, consisting of 150 cases (with 13 cases removed as outliers), was divided into two subsets: a training set (comprising 80% of the data, totaling 120 samples) used for constructing predictive models, and a test set (representing 20% of the data, totaling 30 samples) for external validation to assess model performance. We implemented six distinct ML algorithms: logistic regression,



neural network, random forest, gradient boosting, decision tree, and support vector machine. These algorithms under-

went training using a 10-fold cross-validation approach.

3) Model validation

The primary metric for evaluating model performance was the calculation of the area under the curve (AUC), determined for both the training and test datasets. We focused on the target class, calculating averages across all classes. Additionally, we considered secondary indicators of model performance, including classification accuracy, recall, precision, and F1 score (which combines recall and precision harmoniously), for both the training and test data, also with the same target class being the average across all classes. We categorized the predictive model's performance as excellent ($AUC \geq 0.9$), good (AUC between 0.8 and 0.9), fair (AUC between 0.7 and 0.8), or poor ($AUC < 0.7$) based on the AUC value.²¹

To confirm the significance of each predictive variable, we calculated the importance of feature permutation using the training data. This analysis assessed the contribution of each feature to the model's performance, measuring its impact on the F1 score and, consequently, any increase in the model's prediction error.

RESULTS

FWs characteristics

A total of 150 FWs (60 men and 90 women) were in-

cluded in the ML analysis, with a PPH proportion of 57.3%. Means and standard deviations of VAS for UT pain intensity was 51.68 ± 20.00 and 50.88 ± 19.10 in FWs with and without PPH, respectively. The means and standard deviations of all variables are provided in Table 1.

Predictive models of ML

The performance of the six ML models for predicting the PPH during model training and testing is shown in Tables 2, and the most important predictors of the best performance in gradient boosting and of logistic regression are described in Figure 3, respectively.

Six ML models in the training dataset classified FWs with and without PPH, performed in the order of high AUC, gradient boosting (AUC, 0.812 [good]; F1, 0.786; accuracy, 0.792), random forest (AUC, 0.809 [good]; F1, 0.765; accuracy, 0.775), neural network (AUC, 0.675 [poor]; F1, 0.639; accuracy, 0.650), logistic regression (AUC, 0.665 [poor]; F1, 0.622; accuracy, 0.633), decision tree (AUC, 0.653 [poor]; F1, 0.643; accuracy, 0.642), and support vector machine (AUC, 0.577 [poor]; F1, 0.623; accuracy, 0.650) (Table 2 and Figure 4). In the test dataset classification of FWs with and without PPH, six ML prediction models were performed in the following order: high AUC, gradient boosting (AUC, 0.867 [good]; F1, 0.722; accuracy, 0.766), random forest (AUC, 0.822 [good]; F1, 0.778; accuracy, 0.733), logistic regression (AUC, 0.613 [poor]; F1,

Table 2. Performance metrics of six machine learning algorithms in the training and test set

Performance metrics of six machine learning algorithms in the training set					
Model	AUC	CA	F1	Precision	Recall
Gradient boosting	0.812	0.792	0.786	0.795	0.792
Random forest	0.809	0.775	0.765	0.783	0.775
Neural network	0.675	0.650	0.639	0.642	0.650
Logistic regression	0.665	0.633	0.622	0.624	0.633
Decision tree	0.653	0.642	0.643	0.645	0.642
Support vector machine	0.577	0.650	0.623	0.645	0.650
Performance metrics of six machine learning algorithms in the test set					
Model	AUC	CA	F1	Precision	Recall
Gradient boosting	0.867	0.766	0.722	0.619	0.867
Random forest	0.822	0.733	0.778	0.667	0.933
Logistic regression	0.613	0.567	0.629	0.550	0.733
Decision tree	0.538	0.533	0.562	0.529	0.600
Support vector machine	0.493	0.467	0.619	0.481	0.867
Neural network	0.467	0.433	0.564	0.458	0.733

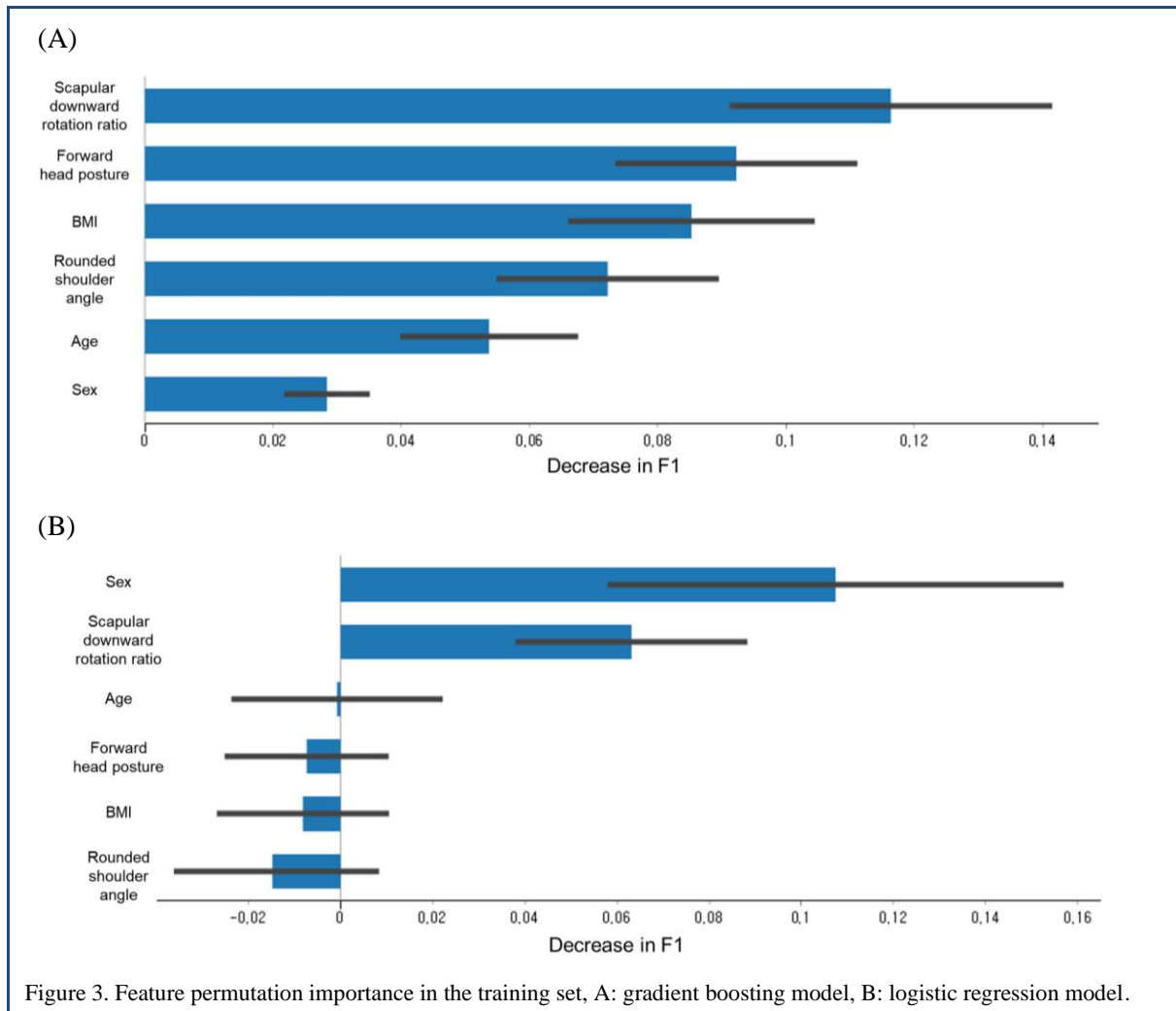


Figure 3. Feature permutation importance in the training set, A: gradient boosting model, B: logistic regression model.

0.629; accuracy, 0.567), decision tree (AUC, 0.538 [poor]; F1, 0.562; accuracy, 0.533), support vector machine (AUC, 0.493 [poor]; F1, 0.619; accuracy, 0.467) and neural network (AUC, 0.467 [poor]; F1, 0.564; accuracy, 0.433) (Table 2).

Regarding feature permutation importance, scapular downward rotation ratio, forward head posture, BMI and rounded shoulder angle were the top four important predictors of PPH in gradient boosting model. The sex, scapular downward rotation ratio, age and forward head posture were the top four important predictors of PPH in the logistic regression (Figure 3).

DISCUSSION

The present study confirmed that the gradient boosting model classified FWs with and without PPH and performed the best AUC among the six ML algorithms, using training data (AUC, 0.812 [good]; F1, 0.786) and test data (AUC, 0.867 [good]; F1, 0.722). Otherwise, logistic regression

model performed the lower AUC than gradient boosting model, using training [AUC, 0.665 (poor); F1, 0.643] and test data [AUC, 0.613 (poor); F1, 0.629]. Traditional statistical methods like logistic or linear regression offer certain benefits, such as creating clinical models that are easy to understand and the availability of various free and commercial software tools for conducting these analyses.^{20,21} However, these methods face limitations when dealing with nonlinear relationships between the outcome (or logit of outcome) and predictors, especially when there's a high number of candidate predictors relative to the sample size.²¹ One significant difference between traditional statistics and machine learning lies in their primary focus: traditional statistics prioritize inference, which involves understanding the data generation process, while machine learning places a greater emphasis on prediction. Machine learning has an advantage in that it offers a range of algorithms capable of modeling highly complex nonlinear relationships. In addition, optimal machine learning models can incorporate multiple interacting factors, allowing for consistent and

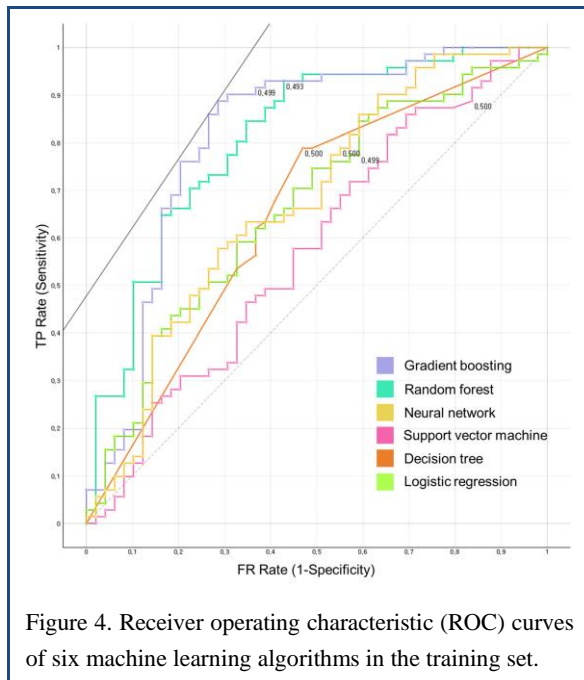


Figure 4. Receiver operating characteristic (ROC) curves of six machine learning algorithms in the training set.

precise predictions, irrespective of whether each factor has been confirmed as an independent risk factor through conventional regression analyses.²⁸

Donatelli (2012) proposed that in order to establish an appropriate treatment plan for shoulder pain, physical therapists or clinicians should conduct an assessment that takes into account the examination of both neck and shoulder posture.¹⁴ This is because incorrect positioning of the neck and scapula can also contribute to neck and shoulder pain. However, because the type of posture analysis that needs to be checked has many elements to check in the three planes (frontal, sagittal and transverse plane), there were no guidelines as to which posture should be evaluated first according to the importance related to PPH. Recently, ML techniques have been applied to patients with musculoskeletal disorders and have been touted to offer superior predictive accuracy compared to traditional statistical methods. Which postural variables is more important for classifying individuals with and without PPH, based on ML techniques? Also, how does machine learning classify PPH through priorities among these variables? The research identifies important predictors for PPH using both ML and logistic regression. In the gradient boosting model, in order of importance, scapular downward rotation ratio, forward head posture, BMI, and rounded shoulder angle emerge as the top predictors. In logistic regression, in order of importance sex, scapular downward rotation ratio, age, and forward head posture play significant roles. These findings shed light on the key factors that may contribute to PPH among FWs. Understanding these predictors can help in designing

targeted interventions to alleviate and prevent PPH.

Interestingly, there were no significant statistical differences between subjects with and without PPH regarding the forward head posture ($p=0.255$), rounded shoulder angle ($p=0.363$), and scapular downward rotation ratio ($p=0.098$). Despite this lack of statistical difference between FWs with and without PPH, gradient boosting showed good performance for classifying FWs with and without PPH. ML excels in the simultaneous analysis of multiple predictive variables, considering their combinations and interactions, without relying on pre-assumed relationships between variables.²⁸ Furthermore, ML places a greater emphasis on producing consistent and precise predictions rather than on interpretability. It also continually improves and self-corrects as the dataset grows over time.²⁹

The study's findings have several clinical and preventive implications. Firstly, the identification of predictive factors can aid healthcare professionals in assessing the risk of PPH in FWs. Individuals with identified risk factors can be closely monitored, and preventive measures, such as posture correction exercises or ergonomic adjustments, can be implemented early to reduce the likelihood of PPH development. Secondly, the superiority of ML models in classification suggests the potential for developing automated screening tools that can quickly and accurately assess PPH risk in FWs. While this study provides valuable insights into PPH classification among FWs, there are opportunities for further research. Future studies could explore additional factors, such as work-related stress, physical activity levels, and ergonomic conditions, to gain a more comprehensive understanding of PPH in this occupational group. Moreover, longitudinal studies tracking the progression of musculoskeletal pain and PPH over time would be beneficial in identifying causal relationships and effective intervention strategies.

We should recognize certain limitations of this study. The sample primarily comprised FWs, which might restrict the applicability of the results to different groups. Also, the study's cross sectional nature, relying on existing data, might introduce selection bias and confounding variables. Future research in this field could emphasize prospective studies involving more diverse populations and incorporating additional clinical variables. There's a need for further exploration of the mechanisms that underlie the connection between postural variables and PPH.

CONCLUSION

This study focused on musculoskeletal pain in FWs, particularly in the neck and shoulders, and aimed to classify

PPH using ML compared to logistic regression. The research identified that the gradient boosting ML model performed best in classifying PPH, highlighting the importance of factors like scapular downward rotation ratio, forward head posture, BMI, and rounded shoulder angle. While no statistical differences were found in certain postural variables between those with and without PPH, ML models demonstrated their classification power. This research has potential implications for early intervention and risk assessment in PPH among FWs, possibly leading to automated screening tools. This research contributes significantly to the field of occupational health by highlighting the prevalence of musculoskeletal pain among FWs and offering advanced machine learning techniques for the classification of pressure pain hypersensitivity. The identification of significant predictors and the potential for automated screening tools hold promise for improving the well-being of FWs and reducing the burden of musculoskeletal pain in this profession.

Key Points

Question Will there be a difference in performance between classical statistical models and ML in classifying PPH? What are the key postural factors contributing to musculoskeletal pain, specifically PPH, in FWs?

Findings ML models, specifically gradient boosting, outperformed traditional logistic regression in classifying FWs with and without PPH. Key predictors for PPH included scapular downward rotation ratio, forward head posture, BMI, and rounded shoulder angle. Despite no statistical differences in postural variables between FWs with and without PPH, ML models demonstrated their classification power.

Meaning Machine learning models, such as gradient boosting, offer superior classification performance for identifying FWs with and without PPH compared to traditional logistic regression. These findings have potential implications for early intervention, risk assessment, and the development of automated screening tools to improve the well-being of FWs and reduce musculoskeletal pain in this profession.

Article information

Conflict of Interest Disclosures: The authors declare that they have no competing financial interests or personal relationships that may have influenced the work reported in this study.

Funding/Support: None.

Acknowledgment: We are grateful to my colleagues who study and research for machine learning together in Laboratory of KEMA AI Research (KAIR).

Ethic Approval: This research protocol was granted approval by the Yonsei University Mirae Campus Institutional Review Board (certification number: #1041849–201603-BM-005–02).

Author contributions

Conceptualization: UJ Hwang.

Data acquisition: UJ Hwang, GT Gwak.

Design of the work: UJ Hwang.

Data analysis: UJ Hwang, GT Gwak.

Project administration: UJ Hwang.

Interpretation of data: GT Gwak.

Writing – original draft: UJ Hwang.

Writing–review&editing: UJ Hwang.

Additional contributions: UJ Hwang, GT Gwak.

REFERENCES

1. Chyuan JYA, Du CL, Yeh WY, Li C-Y. A cross-sectional study of musculoskeletal disorders in relation to work movement characteristics among hotel foodservice employees in Taiwan. *Taiwan J. Public Health*. 2002;21(2):140-149.
2. Chyuan J. Risk factors associated with work-related musculoskeletal discomfort among commissary food-service workers. *Taiwan J. Public Health*. 2005;24:154-161.
3. Haukka E, Leino-Arjas P, Solovieva S, Ranta R, Viikari-Juntura E, Riihimäki H. Co-occurrence of musculoskeletal pain among female kitchen workers. *Int Arch Occup Environ Health*. 2006;80(2):141-148.
4. Hwang U-J, Kwon O-Y. Influencing factors of pressure pain hypersensitivity of the upper trapezius in food service workers with nonspecific neck/shoulder myofascial pain: a cross-sectional study. *Medicine*. 2022; 101(31).
5. Chyuan J-YA, Du C-L, Yeh W-Y, Li C-Y. Musculoskeletal disorders in hotel restaurant workers. *Occup Med*. 2004;54(1):55-57.
6. Shiue HS, Lu CW, Chen CJ, et al. Musculoskeletal disorder among 52,261 Chinese restaurant cooks cohort: result from the National Health Insurance Data. *J Occup Health*. 2008;50(2):163-168.
7. Meleger AL, Krivickas LS. Neck and back pain: musculoskeletal disorders. *Neurol Clin*. 2007;25(2):419-438.
8. Chang C-W, Chang K-Y, Chen Y-R, Kuo P-L. Electrophysiologic evidence of spinal accessory neuropathy in patients with cervical myofascial pain syndrome. *Arch Phys Med Rehabil*. 2011;92(6):935-940.
9. Persson A, Brogardh C, Sjolund B. Tender or not tender:

- test-retest repeatability of pressure pain thresholds in the trapezius and deltoid muscles of healthy women. *J Rehabil Med.* 2004;36(1):17-27.
10. Sjörs A, Larsson B, Persson AL, Gerdle B. An increased response to experimental muscle pain is related to psychological status in women with chronic non-traumatic neck-shoulder pain. *BMC Musculoskelet Disord.* 2011; 12(1):230.
 11. Graven-Nielsen T, Arendt-Nielsen L. Assessment of mechanisms in localized and widespread musculoskeletal pain. *Nat Rev Rheumatol.* 2010;6(10):599-606.
 12. Desmeules JA, Cedraschi C, Rapiti E, et al. Neurophysiologic evidence for a central sensitization in patients with fibromyalgia. *Arthritis Rheum.* 2003;48(5): 1420-1429.
 13. Montoya P, Pauli P, Batra A, Wiedemann G. Altered processing of pain-related information in patients with fibromyalgia. *Eur J Pain.* 2005;9(3):293-303.
 14. Donatelli RA. *Physical Therapy of the Shoulder-E-Book.* Elsevier Health Sciences; 2011.
 15. Yip CHT, Chiu TTW, Poon ATK. The relationship between head posture and severity and disability of patients with neck pain. *Man Ther.* 2008;13(2):148-154.
 16. Sahrman SA. *Diagnosis and treatment of movement impairment syndromes.* St. Louis, MO: Elsevier; 2002.
 17. Azevedo DC, de Lima Pires T, de Souza Andrade F, McDonnell MK. Influence of scapular position on the pressure pain threshold of the upper trapezius muscle region. *Eur J Pain.* 2008;12(2):226-232.
 18. Cole AK, McGrath ML, Harrington SE, Padua DA, Rucinski TJ, Prentice WE. Scapular bracing and alteration of posture and muscle activity in overhead athletes with poor posture. *J Athl Train.* 2013;48(1):12-24.
 19. Ha S-m, Kwon O-y, Yi C-h, Jeon H-s, Lee W-h. Effects of passive correction of scapular position on pain, proprioception, and range of motion in neck-pain patients with bilateral scapular downward-rotation syndrome. *Man Ther.* 2011;16(6):585-589.
 20. Rajula HSR, Verlato G, Manchia M, Antonucci N, Fanos V. Comparison of conventional statistical methods with machine learning in medicine: diagnosis, drug development, and treatment. *Medicina.* 2020;56(9):455.
 21. Liew BX, Kovacs FM, Rügamer D, Royuela A. Machine learning versus logistic regression for prognostic modelling in individuals with non-specific neck pain. *Eur Spine J.* 2022;31(8):2082-2091.
 22. Chesterton LS, Sim J, Wright CC, Foster NE. Interrater reliability of algometry in measuring pressure pain thresholds in healthy humans, using multiple raters. *Clin J Pain.* 2007;23(9):760-766.
 23. Jones DH, Kilgour RD, Comtois AS. Test-retest reliability of pressure pain threshold measurements of the upper limb and torso in young healthy women. *J Pain.* 2007;8(8):650-656.
 24. Castro-Sanchez AM, Mataran-Penarrocha GA, Lopez-Rodriguez MM, Lara-Palomo IC, Arendt-Nielsen L, Fernández-de-las-Peñas C. Gender differences in pain severity, disability, depression, and widespread pressure pain sensitivity in patients with fibromyalgia syndrome without comorbid conditions. *Pain Med.* 2012;13(12): 1639-1647.
 25. Lucas KR, Polus BI, Rich PA. Latent myofascial trigger points: their effects on muscle activation and movement efficiency. *J Bodyw Mov Ther.* 2004;8(3):160-166.
 26. Hwang U-J, Kwon O-Y, Yi C-H, Jeon H-S, Weon J-H, Ha S-M. Predictors of upper trapezius pain with myofascial trigger points in food service workers: The STROBE study. *Medicine.* 2017;96(26).
 27. Straker LM, O'Sullivan PB, Smith AJ, Perry MC. Relationships between prolonged neck/shoulder pain and sitting spinal posture in male and female adolescents. *Man Ther.* 2009;14(3):321-329.
 28. Ye Z, Zhang T, Wu C, et al. Predicting the objective and subjective clinical outcomes of anterior cruciate ligament reconstruction: a machine learning analysis of 432 patients. *Am J Sports Med.* 2022;50(14):3786-3795.
 29. Ramkumar PN, Luu BC, Haerberle HS, Karnuta JM, Nwachukwu BU, Williams RJ. Sports medicine and artificial intelligence: a primer. *Am J Sports Med.* 2022; 50(4):1166-1174.