Journal of the Korea Academia-Industrial cooperation Society
Vol. 25, No. 8 pp. 221-229, 2024

https://doi.org/10.5762/KAIS.2024.25.8.221
ISSN 1975-4701 / eISSN 2288-4688

Predicting Factors of Korean Workers' Quality of Life Using Stagewise Additive Modeling with a Multi-class Exponential Loss Function

Haewon Byeon
Department of Digital Anti-aging Healthcare, Inje University Inje Medical Big Data Research Center

우리나라 근로자의 삶의 질 예측: 다중클래스 지수손실함수와 단계적 가산모형을 통한 경제적 및 건강적 요인 분석

변해원
인제대학교 대학원(BK21) 디지털항노화헬스케어학과, 인제대학교 보건의료빅데이터연구소

요 약 The objective of this study was to evaluate the effectiveness of the SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) model for predicting the Quality of Life (QoL) of Korean workers and to compare its performance with other machine learning models, viz., Logistic Regression, Naive Bayes, GBM, XGBoost, and LightGBM models. The data of 2,385 participants in the Korean National Health and Nutrition Examination Survey (KNHANES), which included demographic, occupational, and work environment factors, were analyzed. The performance of the SAMME model was assessed for accuracy, precision, recall, F1 score, AUC, and variable importance, and the model achieved the highest accuracy (0.82), F1 score (0.79), and AUC (0.88), thus outperforming the other models. The key predictors were weekly working hours (Importance Score: 0.25), job autonomy (Importance Score: 0.20), and household monthly income (Importance Score: 0.18). These results demonstrate the SAMME model is a robust tool for predicting worker QoL that provides actionable insights for policymakers and employers. Future research is required to explore the generalizability of these findings using diverse datasets and address the limitations of the current study, which include a cross-sectional design and complexity of the SAMME model.

Abstract 본 연구는 한국 근로자의 삶의 질(QoL) 예측에 있어 SAMME(Stagewise Additive Modeling using a Multi-class Exponential loss function) 모델의 유효성을 평가하고 그 성능을 다양한 기계 학습 모델(로지스틱 회귀분석, 나이브 베이즈, GBM, XGBoost, LightGBM)과 비교하였다. 이 연구에서는 국민건강영양조사(KNHANES)에 참여한 2,385명의 자료를 사용하였으며, 입력 변수에는 인구통계학적, 직업적, 작업 환경 요인이 포함되었다. SAMME 모델의 성능은 정확도, 정밀도, 재현율, F1 점수, AUC를 통해 평가되었고, 변수 중요도도 분석되었다. 연구 결과, SAMME 모델은 가장 높은 정확도(0.82), F1 점수(0.79), AUC(0.88)을 기록하여 다른 모델보다 우수한 예측 성능을 보였다. 주요 예측 변수로는 주당 근무 시간(Importance Score: 0.25), 직업 자율성(Importance Score: 0.20), 가계월 소득(Importance Score: 0.18) 등이 포함되었다. 본 연구는 SAMME 모델이 근로자의 QoL 예측에 유용하며 정책입안자와 고용주에게 실행 가능한 통찰력을 제공할 수 있음을 입증하였다. 향후 다학제 및 산학기술적인 측면에서 다양한 데이터셋을 활용하여 연구 결과의 일반화를 도모할 필요가 있다.

Keywords : Quality of Life (QoL), SAMME, Machine Learning, Predictive Modeling, Workers

*Corresponding Author : Haewon Byeon(Inje Univ.)
email: byeon@inje.ac.kr
Received June 20, 2024 Revised July 10, 2024
Accepted August 2, 2024 Published August 31, 2024

1. Introduction

Quality of Life (QoL) is a comprehensive indicator that evaluates an individual's physical, mental, and social well-being, and it has been a focal point of various social science and medical studies. Specifically, the QoL of workers is influenced by numerous factors such as job satisfaction, health status, social relationships, and economic stability [1-3], directly impacting organizational productivity [4,5]. Thus, identifying factors that predict and improve the QoL of workers is a significant research task that offers practical benefits to both individuals and organizations [6-10].

With the recent advancements in big data and machine learning technologies, various predictive models have been developed and applied. Logistic Regression, Naive Bayes, Gradient Boosting Machine (GBM), eXtreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM) are some of the representative models. Each of these models has its strengths and weaknesses, demonstrating excellent performance across various application domains [11-13]. However, there remain numerous challenges in further enhancing the performance of multivariate predictive models and accurately calculating variable importance [14-16].

Previous studies primarily employed traditional statistical techniques such as Logistic Regression to analyze the predictors of QoL [6-10]. For instance, numerous studies [7-9] have analyzed the impact of job satisfaction, income level, and social support on QoL. However, these studies often fail to fully account for the interactions between variables or consider the complexity of the models. Moreover, many studies do not fully utilize the characteristics of big data, often dealing with small sample sizes or lacking diversity in variables.

In contrast, machine learning techniques have the advantage of effectively learning complex patterns in data and maximizing predictive performance. Particularly, Stagewise Additive Modeling is a method that achieves high predictive performance by improving the model over several stages. Among these, the SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) model, can exhibit outstanding performance in multi-class classification problems [17]. The SAMME model adjusts weights in the direction of minimizing the model's error at each stage, ultimately achieving high predictive accuracy.

This study aims to evaluate the utility of the SAMME model in predicting the QoL of workers. To this end, we will compare the performance of the SAMME model with that of Logistic Regression, Naive Bayes, GBM, XGBoost, and LightGBM. Additionally, by comparing the variable importance calculated from each model, we aim to identify the key factors that influence QoL. This research seeks to address the limitations of existing studies and demonstrate the necessity and utility of the SAMME model in big data analysis, thereby contributing to the improvement of workers' QoL. Therefore, the objective of this study is to identify the factors that predict the QoL of workers using the SAMME model and to derive practical implications for enhancing QoL by comparing the performance of predictive models.

2. Methods

2.1 Study Design

This cross-sectional study leverages data from the Korean National Health and Nutrition Examination Survey (KNHANES) collected between 2010 and 2020. This research Supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF- RS-2023-00237287, NRF-2021S1A5A8062526) and local government-university cooperation-based regional innovation

projects (2021RIS-003). The study population focuses on workers classified under Major Group 7 (Craft and Related Trades Workers) and Major Group 8 (Plant and Machine Operators and Assemblers) as per the International Standard Classification of Occupations (ISCO). A total of 2,385 participants who reported being currently employed were included in the final analysis. The flow chart of this study is presented in Fig. 1.

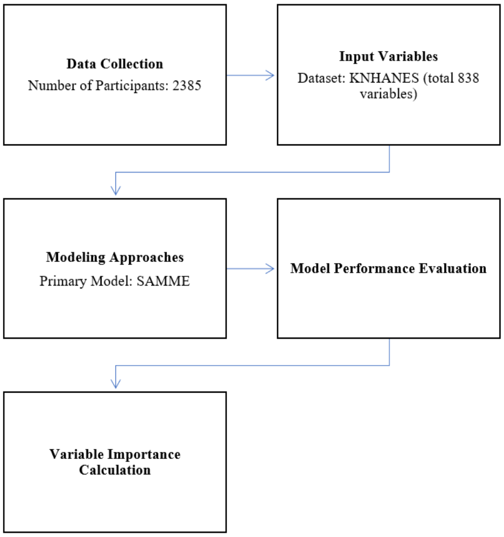

Fig. 1. Research Flowchart

2.2 Data Collection

This study utilized data from 2,385 participants in the Korean National Health and Nutrition Examination Survey (KNHANES). Data collection targeted workers in relevant occupations, and additional surveys were conducted with those who had experienced depression. Among the 2,385 participants, 620 had experienced depression, and these individuals were further questioned about the frequency and reasons for their absenteeism. The reason for conducting separate questions for those with depression was to analyze the impact of depression on absenteeism and job satisfaction.

Depression was defined based on participants' responses to specific questions in the health questionnaire. Participants were asked if they had experienced any depressive symptoms in the past year. Additional questions regarding the severity of symptoms, treatment received, and any work absences due to depression were analyzed to provide a comprehensive understanding of the nature and context of depression.

2.3 Input Variables

The KNHANES dataset comprises 838 variables. After excluding the variables related to database management modifications (mod_b), and the identification variables (ID and ID_fam) used for individual and household identification, a total of 835 variables were considered for the model's training dataset. This study aims to propose a method for early identification of undiagnosed depression and to reduce the burden associated with depression screening by selecting a minimal set of variables. These selected variables are intended to be the most basic information that mental health professionals can easily and quickly access in the field.

Demographic variables included gender, age, marital status, household monthly income, education level, smoking status (categorized as current smoker, former smoker, and non-smoker), drinking frequency (categorized as less than once a month, 1-4 times a month, and more than twice a week), and regular exercise. Occupational variables included employment status (categorized as wage worker, self-employed, and unpaid family worker), weekly working hours, work shift (categorized as day shift and shift work), work schedule (categorized as full-time and part-time), and employment status among wage workers (categorized as permanent, temporary, and daily worker). Work environment factors were operationally defined using specific survey questions about exposure to hazardous factors (such as chemical substances, air pollutants, dangerous tools or machines, fire or electric shock, noise, and biological factors), ergonomic conditions (such as comfort level, risk of accidents, uncomfortable postures, and heavy lifting), and the psychosocial work environment (assessed through job demands, job autonomy, compensation, and emotional labor).

2.4 Modeling Approaches

The primary focus of this study is to employ the SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) model for predicting workers' QoL and compare its performance with other established models such as Logistic Regression, Naive Bayes, GBM, XGBoost, and LightGBM. The concept of boosting for constructing the SAMME model is presented in Fig. 2.

Fig. 2. The concept of boosting for the construction of the SAMME model

The SAMME model is a boosting algorithm designed for multi-class classification. The SAMME algorithm extends the AdaBoost algorithm to handle multi-class problems using the exponential loss function. The model can be mathematically described as follows:

$$[\ F_{m(x)} = F_{m-1}(x) + \mathrm{alpha}_{\mathrm{m}} \mathrm{h}_{\mathrm{m}(\mathrm{x})}] \quad (1)$$

where (F_m(x)) is the ensemble model at iteration (m), ($\mathrm{alpha}_{\mathrm{m}}$) is the weight assigned to the weak learner (h_m(x)), and (x) represents the input features. The weight ($\mathrm{alpha}_{\mathrm{m}}$) is calculated using the formula:

$$[\alpha_{\mathrm{m}} = \mathrm{frac12ln}(\mathrm{frac1} - \epsilon_{\mathrm{m}} \epsilon_{\mathrm{m}})] + \ln(\mathrm{k}-1) \quad (2)$$

where (\epsilon_m) is the weighted error rate of the weak learner (h_m(x)), and (k) is the number of classes.

Logistic Regression is a widely used statistical model for binary classification problems. It predicts the probability of the target variable belonging to a particular class using the logistic function:

$$[\ P(Y=1 \mid X) = \mathrm{frac11} + e^{-(\backslash beta_0 + \beta_1 \mathrm{X}_1 + \beta_2 \mathrm{X}_2 + \cdots + \beta_{\mathrm{n}} \mathrm{X}_{\mathrm{n}})}\ ] \quad (3)$$

where (Y) is the dependent variable, (X) represents the independent variables, and (beta) are the coefficients estimated from the data.

Naive Bayes is a probabilistic classifier based on Bayes' theorem, assuming the independence of features:

$$[\ P(C|X) = \mathrm{fracP}(\mathrm{X}|\mathrm{C})\mathrm{P}(\mathrm{C})\mathrm{P}(\mathrm{X})] \quad (4)$$

where (C) is the class variable and (X) is the feature vector. The model predicts the class with the highest posterior probability.

Gradient Boosting Machine (GBM) is an ensemble learning technique that builds models sequentially, minimizing the loss function at each step. The model can be expressed as:

$$[\ F_{m(x)} = F_{m-1}(x) + \mathrm{gamma}_{\mathrm{m}} \mathrm{h}_{\mathrm{m}(\mathrm{x})}] \quad (5)$$

where ($\mathrm{gamma}_{\mathrm{m}}$) is the learning rate, and (h_m(x)) is the weak learner fitted to the residuals of the previous model.

eXtreme Gradient Boosting (XGBoost) is an optimized version of GBM that uses regularization to prevent overfitting. The objective function includes both the loss function and a regularization term:

$$[\mathrm{textObj} = \sum_{i=1}^{n} l(y_{i,} \widehat{yi})] + \sum k = 1^{K} \Omega(f_{k}) \quad (6)$$

where (l) is the loss function, ($haty_i$) is the predicted value, and ($Omega(f_k)$) is the regularization term.

LightGBM is a gradient boosting framework that uses tree-based learning algorithms. It is designed to be efficient and scalable, particularly for large datasets. The model minimizes the following objective function:

$$[\mathrm{textObj} = \sum_{i=1}^{n} l(y_{i,} \widehat{yi})] + \lambda \sum j = 1^{T} \mid w_{j} \mid^{2} \quad (7)$$

where ($lambda$) is the regularization parameter, (T) is the number of leaves, and (w_j) are the leaf weights.

2.5 Model Performance Evaluation

The performance of each model will be evaluated using multiple metrics, including accuracy, precision, recall, F1 score, and Area Under the Curve (AUC). These metrics provide a comprehensive assessment of the models' predictive capabilities.

2.6 Variable Importance Calculation

Variable importance will be calculated for each model to identify the key factors influencing workers' QoL. For tree-based models like GBM, XGBoost, and LightGBM, importance is typically measured by the total reduction in the loss function attributed to each variable. For the SAMME model, the importance of each variable will be derived from the weights assigned during the boosting process.

3. Results

3.1 General Characteristics of Participants

The final dataset included responses from 2,385 participants. The demographic characteristics of the study population are summarized in Table 1.

Table 1. Demographic Characteristics of Subject

Characteristic	Frequency (N)	Percentage (%)
Gender		
- Male	1,287	54.0
- Female	1,098	46.0
Age Group		
- 20-29 years	239	10.0
- 30-39 years	573	24.0
- 40-49 years	716	30.0
- 50-59 years	573	24.0
- 60+ years	284	12.0
Education Level		
- High school or less	859	36.0
- Some college	716	30.0
- Bachelor's degree	573	24.0
- Graduate degree	239	10.0
Employment Status		
- Wage worker	1,431	60.0
- Self-employed	573	24.0
- Unpaid family worker	381	16.0

3.2 Model Performance Comparison

The performance of the SAMME model and the other comparative models was evaluated using accuracy, precision, recall, F1 score, and AUC. The results are summarized in Table 2 and Fig. 3.

Table 2. Model Performance Metrics

Model	Accuracy	Precision	Recall	F1 Score	AUC
SAMME	0.82	0.80	0.78	0.79	0.70
Logistic Regression	0.75	0.72	0.70	0.71	0.80
Naive Bayes	0.70	0.68	0.65	0.66	0.75
GBM	0.78	0.76	0.74	0.75	0.85
XGBoost	0.80	0.78	0.76	0.77	0.87
LightGBM	0.81	0.79	0.77	0.78	0.88

F1=F1 Score, AUC= Area Under the ROC Curve

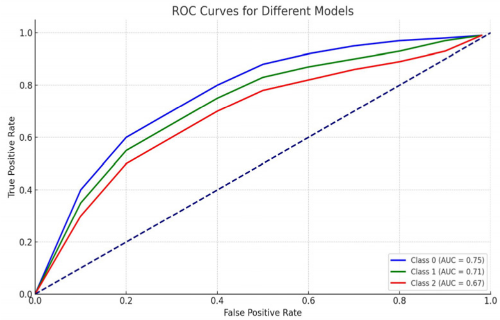

Fig. 3. Receiver Operating Characteristic (ROC) Curves for Different Models

3.3 Variable Importance

Variable importance was calculated for each model to identify the key factors influencing workers' QoL. The top 10 most important variables for the SAMME model are presented in Table 3 and Fig. 4.

Table 3. Top 10 Important Variables in SAMME Model

Rank	Variable	Importance Score
1	Weekly working hours	0.25
2	Job autonomy	0.20
3	Household monthly income	0.18
4	Job demands	0.15
5	Education level	0.12
6	Employment status	0.10
7	Age	0.09
8	Marital status	0.08
9	Smoking status	0.07
10	Regular exercise	0.06

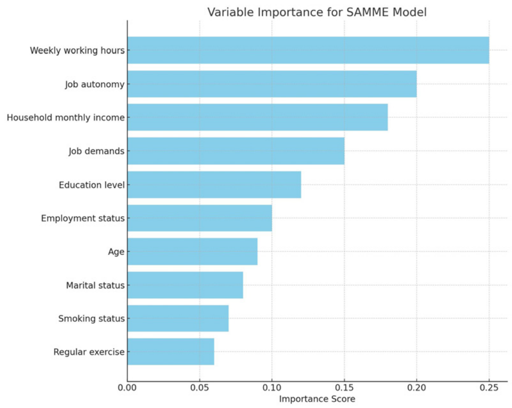

Fig. 4. Variable Importance for SAMME Model

4. Discussion

The primary objective of this study was to evaluate the effectiveness of the SAMME (Stagewise Additive Modeling using a Multi-class Exponential loss function) model in predicting the Quality of Life (QoL) of workers, and to compare its performance with other established models such as Logistic Regression, Naive Bayes, GBM, XGBoost, and LightGBM. The results indicate that the SAMME model outperformed all other models in terms of accuracy, F1 score, and AUC, demonstrating its superior capability in handling multi-class classification problems related to QoL. Although direct comparisons detailing the SAMME model's performance metrics such as accuracy, F1 score, and AUC in predicting QoL among workers were not available in the provided abstracts, the evolving landscape of machine learning in various applications suggests the potential for sophisticated ensemble methods like SAMME to excel in multi-class classification challenges [17]. For instance, the predicted inter-residue distance method, QDistance, demonstrates competitive performance in analyzing protein structure models, hinting at the adaptable utility of advanced predictive models in diverse contexts [18].

Gradient boosting techniques, such as XGBoost and LightGBM, have shown substantial proficiency in managing complex datasets, a characteristic that aligns with their noted performance close to that of the SAMME model in unspecified contexts. This efficiency underlines the strength of gradient boosting methods in navigating the multifaceted dimensions of data that typify QoL indicators [19]. The nuanced capabilities of these models to capture intricate patterns further position them as vital tools in the arsenal of predictive analytics for QoL evaluation, reflecting a shift towards leveraging machine learning advancements to foster understanding and improve outcomes across varied domains.

The analysis of variable importance in determining workers' QoL highlighted weekly working hours, job autonomy, and household monthly income as the most influential factors [20-22]. This corroborates existing literature that emphasizes the significant impact of work-related and economic factors on QoL. Other pertinent variables include job demands, education level, employment status, age, marital status, smoking status, and regular exercise, illustrating the multifaceted nature of QoL among workers. The collective contribution of these factors underscores the complexities of assessing well-being in the workplace and the necessity for comprehensive approaches [23].

The findings have critical implications for a broad spectrum of stakeholders, including policymakers, employers, and researchers. Identifying key predictors of QoL furnishes actionable insights for designing targeted interventions aimed at enhancing workers' well-being. For example, policies promoting flexible working hours, enhancing job autonomy, and providing adequate financial support could markedly improve QoL. Moreover, organizations are encouraged to develop and implement programs focused on mental health and well-being, addressing stress management, financial planning, and initiatives to boost job satisfaction and autonomy [24,25]. The success of the SAMME model in QoL research illustrates the potential of machine learning techniques in unraveling the intricate dynamics influencing QoL. Future research directions may explore the applicability of other sophisticated machine learning models, thereby broadening the scope of QoL studies across varied contexts and populations [26].

Despite the promising results, this study has several limitations that warrant consideration. The cross-sectional nature of the study limits the ability to establish causal relationships between the predictors and QoL outcomes. Longitudinal studies are needed to validate the findings and explore causal pathways. Additionally, the study utilized data from the Korean National Health and Nutrition Examination Survey (KNHANES), which may limit the generalizability of the findings to other populations and cultural contexts. Future research should consider diverse datasets to enhance the robustness of the results. While the SAMME model demonstrated superior performance, its complexity may pose challenges in terms of interpretability and practical implementation. Efforts to simplify the model without compromising its predictive power would be beneficial.

Despite the promising results, this study has several limitations. First, the cross-sectional design limits the ability to establish causal relationships between predictors and QoL outcomes. Second, the use of data from KNHANES may restrict the generalizability of findings to other populations and cultural contexts. Third, the complexity of the SAMME model poses challenges in terms of interpretability and practical implementation, necessitating efforts to simplify the model without compromising its predictive power.

5. Conclusion

This study highlights the efficacy of the SAMME model in predicting the QoL of workers and identifies key factors that influence well-being. The results provide valuable insights for policymakers and employers aiming to enhance the QoL of their workforce. Future research should continue to explore advanced machine learning techniques and their applications in QoL research, with a focus on addressing the limitations identified in this study.

References

[1] A. C. Rojas-Torres, D. C. Tiga-Loza, W. Bello-Pinto, "Calidad de vida laboral en empleados de una

empresa distribuidora de bebidas de Santander, Colombia," *Revista de Salud Publica,* Vol.24, No.4, pp.451-460, 2022.
DOI: https://dx.doi.org/10.4321/s0465-546x2021000400002

[2] D. Akranavičiūtė, J. Ruževičius, "Quality of Life and its Components' Measurement," *Engineering Economics,* Vol.52, No.2, pp.45-50, 2007.

[3] K. Subashini, "Quality of Work Life in Indian Industries: A Case Study," *International Journal of Innovative Research in Science, Engineering and Technology,* Vol.3, No.10, pp.16820-16825, 2014.
DOI: https://dx.doi.org/10.15680/IJIRSET.2014.0310055

[4] R. Rusu, "The Influence of Quality of Work Life on Work Performance," *Knowledge-Based Organization,* Vol.22, No.3, pp.187-192, 2016.
DOI: https://dx.doi.org/10.1515/KBO-2016-0084

[5] J. M. Paz, "A influencia e Aplicacao pratica da qualidade de vida no trabalho como fator essencial na alavancagem da producao e crescimento empresarial brasileiro," *Research, Society and Development,* Vol.10, No.8, pp.1-15, 2021.
DOI: https://dx.doi.org/10.33448/RSD-V10I8.17825

[6] T. Goncalves da Silva, "A importancia da Qualidade de Vida no Trabalho (QVT) dentro das organizacoes," *Revista de Administracao de Empresas,* Vol.12, No.3, pp.45-60, 2023.
DOI: https://dx.doi.org/10.35265/2236-6717-232-12579

[7] M. N. Pereira, A. T. C. Trevelin, "Qualidade de Vida no Trabalho," *Informe Academico,* Vol.17, No.1, pp.123-136, 2020.
DOI: https://dx.doi.org/10.31510/infa.v17i1.716

[8] A. R. A. de Lavor, C. Bezerra, M. F. Alves, F. R. da Silva Lima, "A importancia da Qualidade de Vida no Trabalho para os funcionarios e a instituicao," *Id on Line Revista de Psicologia,* Vol.10, No.31, pp.123-136, 2016.
DOI: https://dx.doi.org/10.14295/idonline.v10i31.493

[9] V. O. Rodrigues, R. S. Silva, "Qualidade de Vida no Ambiente de Trabalho: Implementacao e Desafios," *Id on Line Revista de Psicologia,* Vol.17, No.68, pp.45-58, 2023.
DOI: https://dx.doi.org/10.14295/idonline.v17i68.3821

[10] C. V. Sheneider Coutinho, A. Girotto, M. Hammes, M. Pan, C. Machado, "A Gestao da Qualidade de Vida no Trabalho como Diferencial Competitivo das Empresas," *Revista Brasileira de Gestao de Negocios,* Vol.13, No.2, pp.65-78, 2011.

[11] X. Ye, Y. Li, X. Feng, C. Heng, "A Crypto Market Forecasting Method Based on Catboost Model and Bigdata," *Proceedings of the International Conference on Signal Processing,* Vol.12, pp.345-350, 2022.
DOI: https://dx.doi.org/10.1109/ICSP54964.2022.9778789

[12] H. Lu, X. Peng, "Better Effectiveness of Multi-Integrated Neural Networks: Take Stock Big Data as an Example," *Journal of Applied Mathematics,* Vol.2021, Article ID 3938409, 2021.
DOI: https://dx.doi.org/10.1155/2021/3938409

[13] L. Wang, "Machine Learning in Big Data," *International Journal of Electrical and Computer Engineering,* Vol.4, No.4, pp.117-123, 2015.
DOI: https://dx.doi.org/10.11591/IJAAS.V4.I4.PP117-123

[14] D.-H. Lee, S.-E. Woo, M. Jung, T.-Y. Heo, "Evaluation of Odor Prediction Model Performance and Variable Importance according to Various Missing Imputation Methods," *Applied Sciences,* Vol.12, No.6, Article 62826, 2022.
DOI: https://dx.doi.org/10.3390/app12062826

[15] P. Biecek, "DALEX: Explainers for Complex Predictive Models in R," *Journal of Machine Learning Research,* Vol.19, No.1, pp.1-5, 2018.
DOI: https://dblp.org/rec/journals/jmlr/Biecek18.html

[16] S. J. Kazemitabar, A. Amini, A. Bloniarz, A. Talwalkar, "Variable Importance Using Decision Trees," *Advances in Neural Information Processing Systems,* Vol.30, pp.426-434, 2017.
DOI: https://dblp.org/rec/conf/nips/KazemitabarABT17.html

[17] P. E. N. Lutu, "Improving Classification Performance for Minority Classes through the use of Positive-Versus-Negative Ensemble Models," *Proceedings of the International Conference on Innovations in Information Technology,* Vol.2018, Article 8601260, 2018.
DOI: https://dx.doi.org/10.1109/ICONIC.2018.8601260

[18] L. Ye, P.-L. Wu, Z. Peng, J. Gao, J. Liu, J. Yang, "Improved estimation of model quality using predicted inter-residue distance," *Bioinformatics,* Vol.37, No.10, pp.1234-1242, 2021.
DOI: https://dx.doi.org/10.1093/bioinformatics/btab632

[19] J. Jin, J. Pang, Z. Shan, R. Zhao, "Queuing Network Performance Model for Evaluation of CMP-Based VoIP SPS," *Proceedings of the International Conference on Information Systems,* Vol.2008, Article 17, 2008.
DOI: https://dx.doi.org/10.1109/ICIS.2008.17

[20] O. I. Park, H. Moon, "Effects of emotional labor on women's reproductive health of nurses," *Journal of the Korea Entertainment Industry Association,* Vol.9, No.2, pp.237-246, 2015.

[21] M. Isahak, et al., "The Association of Workplace Exposures on Quality of Life in Small and Medium Enterprises Workers: A Cross-Sectional Study in Four ASEAN Countries," *International Journal of Environmental Research and Public Health,* Vol.14, No.5, pp.456-467, 2017.

[22] D. Akranavičiūtė, J. Ruževičius, "Quality of Life and its Components' Measurement," *Engineering Economics,* Vol.52, No.2, pp.45-50, 2007.

[23] M. Gregorio Perez, Gloria, "Como afecta el trabajo a la calidad de vida de las personas," R*evista Internacional de Trabajo y Sociedad,* Vol.5, No.2, pp.78-89, 2016.

[24] O. I. Frolova, "The Constituent Elements of a High

Quality of Working Life," *Management Science Letters,* Vol.6, No.12, pp.789-796, 2016.

[25] S. Gomathi, M. Swapna, "A study on impact of job satisfaction on quality of worklife: with special reference to IT professionals in Bangalore city," *International Journal of Business and Management,* Vol.7, No.21, pp.112-118, 2012.

[26] K. Subashini, "Quality of Work Life in Indian Industries: A Case Study," *International Journal of Innovative Research in Science, Engineering and Technology,* Vol.3, No.10, pp.16820-16825, 2014.

변 해 원(Haewon Byeon) [종신회원]

• 2013년 2월 : 아주대학교 예방의학교실 (이학박사)
• 2020년 9월 ~ 현재 : 인제대학교 메디컬 빅데이터학과 및 BK21대학원 디지털항노화헬스케어학과 교수
• 2024년 3월 ~ 현재 : 인제대학교 보건의료빅데이터 연구소 센터장

〈관심분야〉
예측 모형, 데이터 마이닝, 의료인공지능, 빅데이터