

ORIGINAL ARTICLE

Prediction and comparison of postural discomfort based on MLP and quadratic regression

Jinwon Lee¹  | Jaejin Hwang² | Kyung-Sun Lee³ 

¹School of Mechanical Engineering, Korea University, Seoul, Republic of Korea

²Department of Industrial and Systems Engineering, Northern Illinois University, DeKalb, Illinois, USA

³Division of Energy Resources Engineering and Industrial Engineering, Kangwon National University, Chuncheon, Republic of Korea

Correspondence

Kyung-Sun Lee, Division of Energy Resources Engineering and Industrial Engineering, Kangwon National University, 24341 Chuncheon-Si, Gangwon-Do, Republic of Korea. Email: ksunlee@kangwon.ac.kr

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Abstract

Objective: The objective of this study was to predict postural discomfort based on the deep learning-based regression (multilayer perceptron [MLP] model).

Methods: A total of 95 participants performed 45 different static postures as a combination of 3 neck angles, 5 trunk angles, and 3 knee angles and rated the whole-body discomfort. Two different combinations of variables including model 1 (all variables: gender, height, weight, exercise, body segment angles) and model 2 (gender, body segment angles) were tested. The MLP regression and a conventional regression (quadratic regression) were both conducted, and the performance was compared.

Results: In the overall regression analysis, the quadratic regression showed better performance than the MLP regression. For the postural discomfort group-specific analysis, MLP regression showed greater performance than the quadratic regression especially in the high postural discomfort group. The MLP regression also showed better performance in predicting postural discomfort among individuals who had a variability of subjective rating among different postures compared to the quadratic regression. The deep learning for postural discomfort prediction would be useful for the efficient job risk assessment for various industries that involve prolonged static postures.

Conclusions: The deep learning for postural discomfort prediction would be useful for the efficient job risk assessment for various industries that involve prolonged static postures. This information would be meaningful as basic research data to study in predicting psychophysical data in ergonomics.

KEYWORDS

deep learning, multilayer perception, postural discomfort, regression

1 | INTRODUCTION

Work-related Musculoskeletal Disorders (MSDs) have been an essential issue in numerous industrial fields. The

negative impacts of MSDs have been well described, such as staff wellbeing, quality of life, job satisfaction, economic burden, sickness-related absences and management procedures, and productivity at work.¹ One of the most significant risk factors for developing MSDs is inappropriate or

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awkward postures.^{2,3} Many jobs involve various awkward postures across different industrial sectors.^{4,5} Awkward postures during work negatively impact various body joints. Previous studies have shown that awkward postures were associated with the increased musculoskeletal discomfort and strain of workers.^{6–9}

Musculoskeletal discomfort is often measured as a way to assess the MSDs in various work environments.¹⁰ Discomfort is related to grouped descriptors such as fatigue, pain, and strain in awkward postures. Discomfort could immediately reveal after performing postural activities that involve various joint positions.¹¹ Many previous studies tended to focus on the whole-body discomfort rather than body segment-specific discomfort.^{12,13} According to recent study results, the postural discomfort was greatly affected by the improper posture of a specific joint.¹⁴ Measurement of postural discomfort could also be useful by many researchers and practitioners because it does not require a biosensor or equipment.

Artificial neural networks have been broadly used to predict different body postures and discomfort had developed a prediction model of human reach posture based on psychophysical discomfort data using a regression model.^{15,16} The study on postural discomfort prediction was mainly related to the car seat, car driver, and reach to grasp postures.^{17–19} In recent postural discomfort studies, they had developed a posture discomfort prediction model of awkward working postures in the manual assembly process.²⁰ Hwang and Lee¹⁴ had evaluated the classification of whole-body postural discomfort using cluster analysis.

In a recent study, Lee et al.²¹ compared the accuracies of squat posture classification using conventional machine learning and deep learning. They mentioned that the results obtained using deep learning were superior to those obtained using conventional machine learning. Yang et al.²² classified work-related physical load levels in construction using deep learning models. Deep learning consisted of multiple neural layers for pattern classification or feature learning. Examples of deep learning models included a variety of structures, such as auto-encoders, restricted Boltzmann machines, convolutional neural networks (CNNs), and recurrent neural networks (RNNs).²³ Most studies have been using the deep learning algorithm to predict posture by converting it to three-dimensional postures based on two-dimensional image file data.^{24–26}

Deep learning algorithms have been actively used to predict posture. Some studies have predicted discomfort based on a specific posture, but it was limited to sitting and driver postures. However, a lack of studies predicted the discomfort of various combined postures occurring in the workplace using deep learning algorithms. Therefore, the purpose of this study was to predict the degree of discomfort using a deep learning algorithm based on data on

the discomfort levels of various combined postures that may occur in the workplace.

2 | METHODS

2.1 | Participants

A total of 95 participants (42 males and 53 females) were recruited for this study. The inclusion criteria consisted of: (1) participants did not have a present symptom of the MSD, and (2) participants had no previous history of the MSD. The average and standard deviation of age, height, and weight were 22.5 ± 2.8 years, 170.8 ± 6.5 cm, and 62.1 ± 8.1 kg, respectively.

2.2 | Experimental protocol

A repeated-measures laboratory study was conducted. A total of 45 different postural interactions were performed per participant. These postures were based on the interactions of 3 neck angles (0° , 20° , and 40°), 5 trunk angles (0° , 20° , 40° , 60° , and 80°), and 3 knee angles (0° , 30° , and 60°).¹⁴ The range of angles was determined according to the Rapid Entire Body Assessment (REBA).²⁷ The order of 45 postural interactions was fully randomized to minimize the residual fatigue and systematic bias due to the order.

The research assistant used a goniometer to control each posture of the participant. For each assigned posture, the participant maintained it for 3 s, which was controlled by the beep sound.¹⁴ To minimize the fatigue, a 1-min break was provided between tasks. Right after each posture, participants rated their overall discomfort based on the 10-point Likert scale questionnaire. The lowest number indicated the least discomfort, and the highest number represented the greatest discomfort.

2.3 | Data analysis

Several demographic variables (gender, weight, height) were collected to find variables that influence postural discomfort in addition to various neck angles, trunk angles, and knee angles. Table 1 shows the categorical data and description of each variable. Height, weight, and exercise were expressed by categorization divided into certain sections. Model 1 and model 2 were constructed to verify the model performance according to the difference in variables. Model 1 included all variables (gender, weight, height, exercise, neck angle, trunk angle, knee angle). Model 2 covered the gender and the body segment angles (neck angle, trunk angle, knee angle).

TABLE 1 Categorical data and description of each variable

Categorical value	1	2	3	4	5	6	7	8
Gender	Male	Female						
Weight (kg)	≥40 and <50	≥50 and <60	≥60 and <70	≥70 and <80	≥80 and <90	≥90		
Height (cm)	≥145 and <150	≥150 and <155	≥155 and <160	≥160 and <165	≥165 and <170	≥170 and <175	≥175 and <180	≥180
Exercise	≥1 h per day	No						

To predict the discomfort based on different postural interactions of the neck, trunk, and knee and demographic variables, both polynomial regressions and deep learning-based regression were considered as prediction models. For the polynomial regressions, quadratic polynomial regressions were used to consider nonlinear relationships between postures and discomfort. For the deep learning-based regression, the Multilayer Perceptron (MLP) regression was used.

Figure 1 depicts a neural network architecture to predict postural discomfort. The networks consisted of the combination, including, input layer, hidden layer, batch normalization layer, activation layer, dropout layer, and output layer. The input layer depended on the number of input variables. Hidden layers had 32, 32, 64, 64 nodes, respectively. To make learning fast and stable, batch normalization was performed after the hidden layer. Activation layers utilized tanh function. The dropout layer blocked the signal going to the node of the next layer for robust training. The output layer resulted in postural discomfort.

The dataset of 95 participants was divided into 86 for training (90%) and 9 for testing (10%). Since postural discomfort varied greatly depending on the individual, the training dataset and the testing dataset were divided by considering the maximum, average, and minimum values of independent participants. In order to augment the training datasets, we added Gaussian noise to postural discomfort within a small variation range ($x \pm 0.05 \times \sigma$). In order to be less affected by the randomly segmented training dataset, k-fold cross-validation was employed with $K = 4$. The Adam optimizer Kingma and Ba²⁸ was utilized with a learning rate of 0.001 for training. The batch size was 128, and all models were trained with the root mean square error (RMSE) as a loss function. To prevent overfitting, the model was trained for a maximum of 50 epochs. Our network was developed with python 3.7 and Keras 2.1.

In order to analyze the prediction performance by regression models, regression analysis and classification analysis methods were applied. MLP regression and quadratic regression models were trained with a training dataset (86 participants). Input data of the test dataset (nine participants) estimated the postural discomfort by the pre-trained MLP regression and quadratic regression. For the performance measures to compare and validate two regression models, conventional regression analysis was employed—root mean squared error (RMSE), average & standard deviation, Pearson's correlation coefficient (R). Also, classification analysis was used to categorize various postural discomfort groups with clustering, confusion matrix, and scatter plot. To categorize varying postural discomfort groups, postural discomfort was classified into three levels: low, moderate, and high based on our previous study finding.¹⁴ In

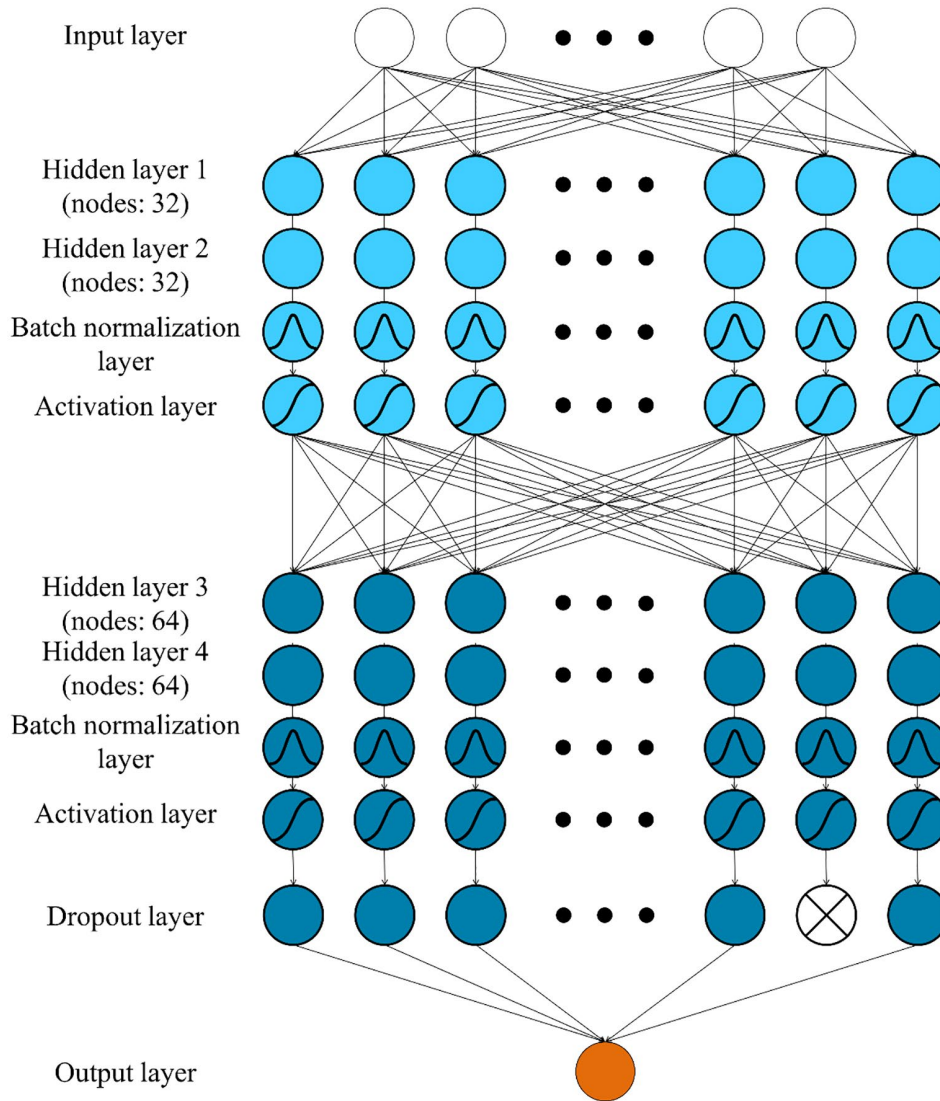


FIGURE 1 Multilayer perceptron network architecture

classification analysis, accuracy, recall, precision, and f1-score were used as the evaluation metrics.²⁹ Accuracy was the number of correctly predicted data divided by the total number of data (1). The recall was a measure of how many truly relevant results were returned and could be calculated by the measure of our model correctly identifying true positives (2). The precision was a measure of result relevancy and could be calculated as the ratio between the True Positives and all the Positives (3). F1 Score was the weighted average of precision and recall. Therefore, this score took both false positives and false negatives into account (4).

$$\text{Accuracy} = \frac{\text{True positives} + \text{True Negatives}}{\text{All data}}, \quad (1)$$

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False Negatives}}, \quad (2)$$

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False Positives}}, \quad (3)$$

$$\text{F1 - Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \quad (4)$$

3 | RESULTS

The overall mean and standard deviation of ground truth postural discomfort (reference) was 4.327 (± 2.061). Since there was no big difference between the training curve and the validation curve, over-, under-fitting did not appear to have occurred.

A comparison of conventional regression analysis for Model 1 and Model 2 is shown in Table 2. The quadratic regression showed better performance than the MLP regardless of models 1 and 2. For the comparison between

TABLE 2 Comparison of the performances between models with conventional regression analysis

Model type	Regression	AVG (STD)	RMSE	R
—	Ground truth	4.327 (2.061)	—	—
Model 1	MLP	4.853 (1.845)	1.922	0.555
	Quadratic	4.150 (1.385)	1.599	0.636
Model 2	MLP	5.334 (1.374)	1.902	0.622
	Quadratic	4.335 (1.350)	1.562	0.651

TABLE 3 Comparison of the performances between models with classification analysis

Model type	Regression	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Model 1	MLP	57.28	58.86	57.20	58.02
	Quadratic	57.03	54.14	59.65	56.76
Model 2	MLP	43.95	50.33	54.39	52.28
	Quadratic	57.53	51.11	43.89	47.21

models 1 and 2, MLP showed an increased performance with Model 1 compared to Model 2. For the quadratic regression, there were no practical differences in the performance between models 1 and 2.

Table 3 describes the classification analysis for models 1 and 2. For the accuracy variable, there was no difference between MLP and quadratic regression within model 1, whereas quadratic regression showed higher accuracy than MLP within model 2. For the precision variable, MLP showed higher precision than quadratic regression within model 1, while there was no difference of precision within model 2. For the recall variable, quadratic regression showed higher recall performance than MLP within model 1, whereas there was an opposite pattern within model 2. For F1-Score variable, MLP showed consistently higher values than quadratic regression across models 1 and 2.

Figure 2 described the ground truth and predicted value results as a confusion matrix. The confusion matrix was close to the diagonal matrix illustrating the effectiveness and accuracy of the MLP regression.

Figure 3 illustrates the individual value of the ground truth and predicted values by MLP and quadratic regression using model 1 for postural discomfort. For Figure 3A–C, the X axis indicates the different participant numbers, and the Y axis shows the postures discomfort, including the ground truth, predicted values from the MLP, and quadratic model. In group 3 (high discomfort), the number of data (portion) of the ground truth, MLP, and quadratic regressions were 42 (10.4%), 50 (12.3%), and 16 (4.0%), respectively. In group 2 (moderate discomfort), the ground truth, MLP, and quadratic regressions data sizes were 124 (30.6%), 209 (51.6%), and 209 (51.6%), respectively. In group 1 (low discomfort), the ground truth, MLP, and quadratic regressions data sizes were 239 (59.0%), 146 (36.0%), and 180 (44.4%),

respectively. This difference was not substantial in moderate (Figure 3B) and low discomfort (Figure 3C) groups. As seen in Figure 3D, both MLP and quadratic models overestimated the postural discomfort in the low discomfort group, whereas they underestimated the values in the high discomfort group. For the high discomfort group, the MLP model showed less underestimation magnitude than the quadratic model.

4 | DISCUSSION

In this paper, we predicted the postural discomfort using MLP regression and quadratic regression for model 1 (gender, height, weight, exercise, and body segment angles) and model 2 (gender and body segment angles). To compare the performance between MLP regression and quadratic regression for the postural discomfort, conventional regression analysis and classification analysis were employed. MLP and quadratic regression showed similar performance of the prediction in the moderate postural discomfort group, but MLP showed higher performance than quadratic regression in the high postural discomfort group. Especially, MLP of model 1 classified the high postural discomfort group with an accuracy of 54.76% compared to other prediction methods.

For the overall analysis, quadratic regression tended to show higher performance than MLP. This could be partially related to the distribution of the test dataset. Among the 405 test data, the high postural discomfort group (group 3) of test data was 42, which is only 10%. Also, the average and standard deviation of group 1 (2.960 ± 0.575) and group 2 (5.376 ± 0.878) were concentrated in between 3 and 5. Since quadratic regression finds the average value rather than the group 3 data, the performance is higher than that of MLP.

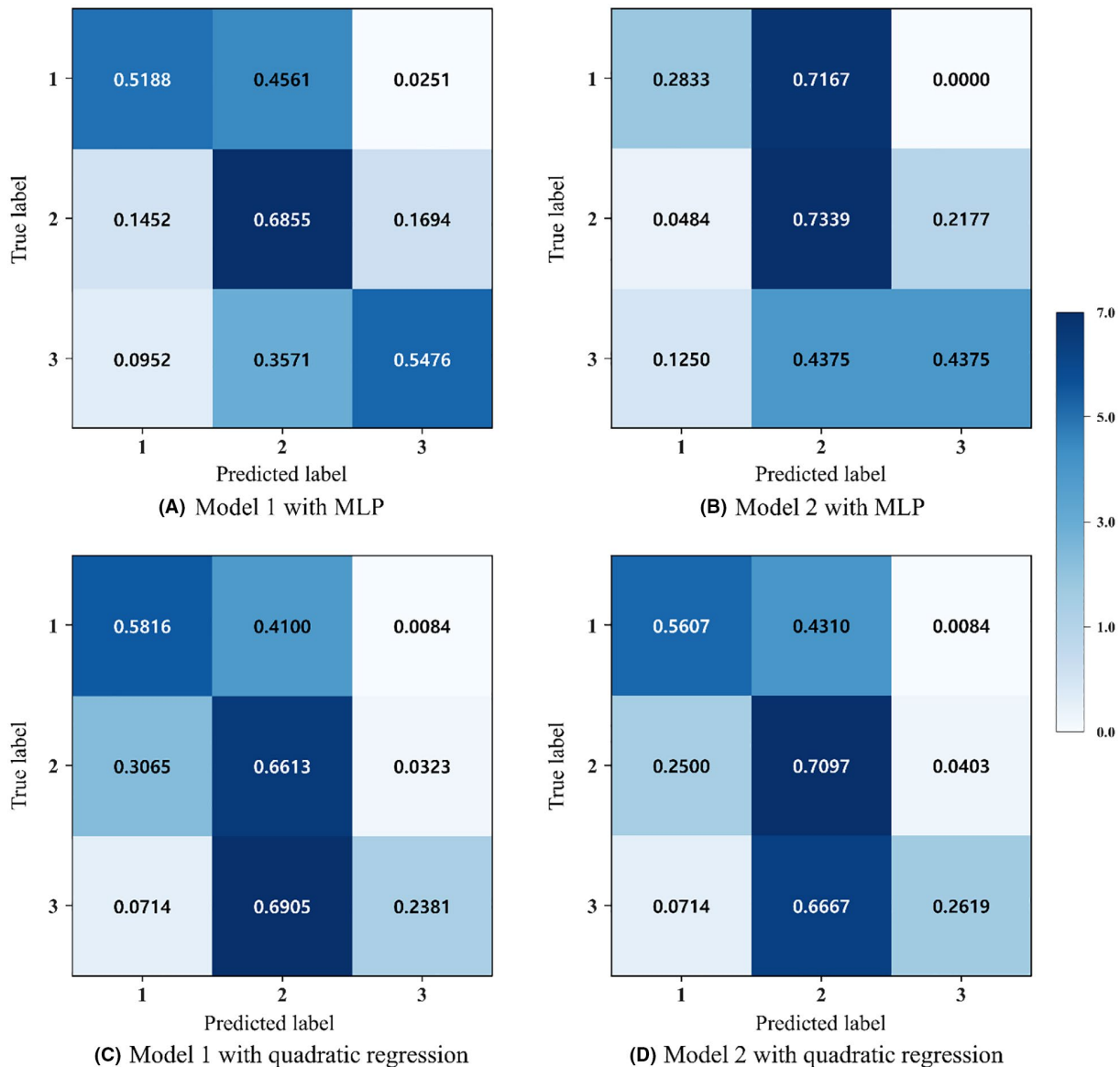


FIGURE 2 Confusion matrix for classification: (A) model 1 with MLP, (B) model 2 with MLP, (C) model 1 with quadratic regression, and (D) model 2 with quadratic regression

Although the quadratic regression showed better performance than MLP overall, there was a different result when analyzing the performance by specific postural discomfort groups. The MLP showed significantly improved performance (24% to 30% higher) than quadratic regression, especially in the high postural discomfort group (group 3). This was also supported by the confusion matrix in Figure 2. In the confusion matrix, the quadratic regression's performance was the highest in the moderate discomfort group (group 2), but there was a dramatic decline of the performance in the high discomfort group (group 3). This indicated that the quadratic regression's prediction was conservative and tended to predict values close to the average values. On the contrary, MLP showed more balanced performance

across three postural discomfort groups. Especially with Model 1, MLP showed only slightly decreased performance in the high postural discomfort group (group 3) compared to the moderate postural discomfort group (group 2). Quadratic regression tended to predict values only within the moderate postural discomfort group regardless of the ground truth. MLP regression classified high postural discomfort values better than quadratic regression. This suggests that MLP would have an advantage in predicting postural discomfort especially in high postural discomfort levels. As shown in Figure 2, the MLP has less accuracy by 7% compared to quadratic regression in low discomfort. However, the MLP showed higher accuracy by 20% than quadratic regression in high discomfort. Especially, workplace injuries and

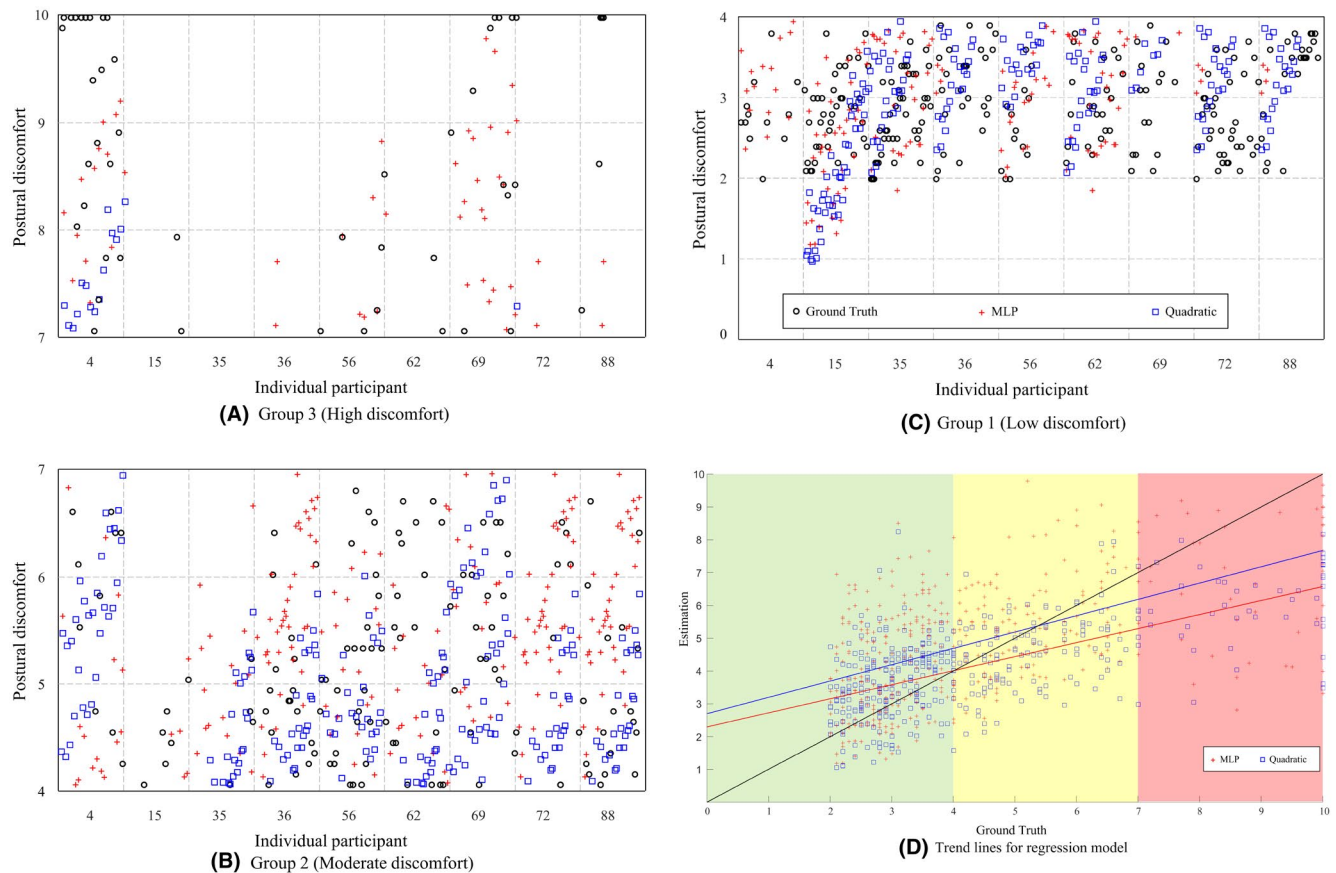


FIGURE 3 Predicted the postural discomfort by MLP and quadratic regressions for model 1: (A) group 3 (high discomfort), (B) group 2 (moderate discomfort), (C) group (low discomfort), and (D) trend lines for regression model. Black circle, red cross, blue rectangle indicates ground truth, MLP, quadratic regression, respectively

health could be more strongly related to high discomfort postures. This indicates the importance of predicting high discomfort postures, as MLP outperformed the quadratic regressions. Since high postural discomfort values would be positively associated with the development of MSDs, the impact of the MLP approach would be expected to be substantial.

The different performance of individual participants between quadratic regression and MLP could also be assessed using scatter plots (Figure 3). When looking at the postural discomfort of the nine participants, some participants gave high scores such as #4 and #69, while others gave low scores such as #35, #36, and #72. High variability of postural discomfort across participants could be related to an individual's perception, sensibility, and physical conditions. Quadratic regression did not capture the variance between individual participants well since their prediction was conservative. As a result, quadratic regression showed a low performance of predicting the postural discomfort of individuals who tended to rate high postural discomfort values and have high variability of postural discomfort among 45 postural conditions. Unlike quadratic regression, MLP showed good prediction results for

participants #4 and #69 in the high postural discomfort group (Figure 3A). As shown in high discomfort group (Figure 3A), MLP predicted more similar to the ground truth compared to quadratic regression, especially for participants of #4, #56, #69, #88. In addition, for the low postural discomfort group (Figure 3C), MLP made accurate predictions for #15 participants who gave low overall postural discomfort scores. This suggests that MLP would have the potential to learn and predict the variability of participant's subjective postural discomfort among different combinations of body postures. This was in line with our previous study showing that MLP showed higher performance in predicting the grip strength compared to linear, quadratic, and cubic regressions, especially for individuals who had high variability of grip strength across conditions.³⁰ This supports the MLP's strength in solving classification and regression problems identified from previous studies.³¹

We predicted subjective postural discomfort by demographic information of participants and body segment angles (neck, trunk, knee) using MLP regression. This prediction of various postural discomfort levels will be useful in various industries that involve prolonged static

postures such as cashiers, surgeons, and dentists. The predictive model developed in this study could be useful to be embedded in the video-based postural assessment tool. Our findings of predicting postural discomfort could advance our fundamental understanding of estimating subjective measurements commonly used in the ergonomics field.

There were several limitations in this study. First, the dataset was built with 95 subjects. Although the present study showed the meaningful results based on this small sample size, further experiments with a larger sample size could yield higher prediction performance. Second, this study did not consider additional properties such as the age of participants and underlying disease that may affect postural discomfort. Since we only recruited university students, we could not train postural discomfort of different age levels of participants. Since age is known as a critical factor affecting the postural discomfort, age-specific prediction of postural discomfort could be studied in the future.³² Lastly, despite of promising results of MLP regression in high postural discomfort groups, the overall prediction performance was deemed low (accuracy is about 57%). The performance could be further improved by adjusting the model structure or utilizing different deep learning algorithms.

5 | CONCLUSION

This study applied the MLP regression and quadratic regression to predict postural discomfort and compared the performance of prediction using conventional regression analysis and classification analysis. Quadratic regression of model 1 (including all variables) revealed a good prediction performance in the conventional regression analysis, and MLP of model 1 showed a great performance in classification analysis. Especially, MLP of model 1 showed a higher accuracy of 54.7% than the other methods (24%~30%), especially in the high postural discomfort group. This information would be meaningful as basic research data to study in predicting psychophysical data in ergonomics.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DISCLOSURE

Ethical approval: The research design in this study was reviewed and passed by the Human Subject Committee. *Informed consent:* all the respondents signed the Human Subject Consent. *Animal Studies:* N/A.

AUTHOR CONTRIBUTIONS

Lee K-S conceived the ideas. Hwang JJ contributed to literature review. Lee K-S collected the data. Lee JW analyzed the data. Lee K-S was involved in research design, literature discussion, and data analysis. Lee K-S, Hwan JJ, and Lee JW led the writing.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

ORCID

Jinwon Lee  <https://orcid.org/0000-0003-4810-1014>

Kyung-Sun Lee  <https://orcid.org/0000-0002-4783-5860>

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