REAL-TIME FAILURE PREDICTION MODELS IN RESISTANCE TRAINING: APPLICATION TO ARM CURL

Beomdo Kim[1], and Jooeun Ahn[1,2,3]

Department of Physical Education, Seoul National University, South Korea[1]
Institute of Sport Science, Seoul National University, South Korea[2]
Soft Robotics Research Center, Seoul National University, South Korea[3]

Resistance training has recently become popular. If failure points, beyond which the intended motion cannot be executed, are reliably predicted, it is possible to increase the efficacy of the training and decrease the risk of injury. We aim to develop machine learning models that can enhance training effects through the proper setting of the rate of perceived exertion and prevent injuries from excessive motion by predicting the failure points. Ten young and healthy adults performed 3 sets of dumbbell arm curl using each arm with a weight of 70% of their one-repetition maximum until they reached the failure point and could not perform the standard arm curl. Using the kinematic features that we collected during each set, we developed failure prediction models based on five classification algorithms. Four models out of the five yielded the accuracy over 90%. Our findings suggest that these models can enhance the training effects by maintaining proper rate of perceived exertion, and prevent injuries due to excessive training load.

KEYWORDS: muscle training, machine learning, failure point prediction, kinematics

INTRODUCTION: Resistance training with dumbbells, barbells, and machines is effective in improving muscular endurance and strength (Winett & Carpinelli, 2001; Wescott, 2012). To prevent injury during this resistance training, which has become popular among the general public as well as athletes, National Strength and Conditioning Association (NSCA) and American College of Sports Medicine (ACSM) suggested guidelines on the appropriate warming up and choice of weights and sets (Pearson et al., 2000; Wolters, 2021). Nevertheless, people who participate in resistance training frequently suffer injuries to their shoulders, backs, and knees due to an excessive load of training (Quatman et al., 2009; Kerr et al., 2010).
According to recent meta-analysis studies, repeating up to failure does not help to improve muscular strength and hypertrophy (Davies et al., 2015; Grgic et al., 2022). Rather than accelerating the training effects, such training can even lead to musculoskeletal injuries (Stone et al., 1996). Therefore, it is critical to predict the failure point before the trainee fails to perform the aimed motion and maintain the proper rate of perceived exertion (RPE).
This study aims to develop machine learning models that predict the failure points in arm curl, one of the most common kinds of resistance training. Considering that kinematics change as the number of repetition approaches the failure point, we collected various kinematic data and attempted to classify the failure data. Using various classification algorithms, we devised real-time failure prediction models that use the kinematic data as the model features.

METHODS: Ten healthy young males (age: 27.22±1.31 years; height: 176±6.07 cm; mass: 80±10 kg) without neuromuscular and orthopaedic injuries participated in the study. This study was approved by Institutional Review Board, and consented by the participants.
We used adjustable dumbbells (NÜOBELL 232, NÜOBELL Inc., Sweden; mass span: 2~32 kg) whose mass can be set for each subject. We fixed the participant's elbow using an arm blaster (Zero to hero, Korea) to prevent the participant from shaking his elbow and torso during arm curl. Kinematic data of reflective markers placed on each arm and dumbbell were recorded at a sampling frequency of 100Hz using nine motion capture cameras (Arqus A5, Qualisys, Sweden). Ten reflective markers were placed on the anatomical landmarks (shoulder, elbow, and wrist) of both arms as shown in Figure 1. Two reflective markers were additionally attached

to the dumbbell. The position data of the markers were used to calculate the angle of the elbow and the kinematic characteristics of the dumbbell.
Prior to the experiment, arm curl one-repetition maximum (1RM) test was performed using a previously described protocol (Kraemer et al., 1995). Subjects warmed up by performing 8~10 repetitions with light weight and 3~5 repetitions with moderate weight. Then, the 1RM test was performed until the subject could no longer perform the full range of motion in a quantitatively defined acceptable posture within 6 attempts. At least 3 minutes of rest were allowed between each maximal attempt.

Figure 1: Equipment and maker placement on the anatomical landmarks

For each participant, the experiment was conducted twice with a minimum interval of 48 hours to ensure sufficient recovery of the muscles used to perform the movement. The participant was instructed to perform standing one arm dumbbell curl with a weight of 70% of his 1RM as fast as possible during concentric contractions without moving his torso. A beat of 12 reps/min was provided to control the speed of motion. On each day of experiment, the participant performed 6 trials (3 trials each with the left and right arm) until he could no longer perform the full range of motion. The participant rested for 3 minutes or more between each trial to recover from the fatigue (Freitas de Salles et al., 2000).
The failure repetition was defined as the repetition in which the elbow angle did not reach 90% of the average range of motion (ROM) of the first 3 repetitions within 5 seconds. Based on this failure criterion, the data from the repetition immediately before the failure repetition were classified as “failure data”; right after the repetition with the failure data, the participant would actually fail. On the other hand, the data from three consecutive repetitions just before the repetition with failure data were classified as success data. Therefore, as illustrated in Figure 2, we obtained 3 sets of success data and 1 set of failure data for each trial; we collected 480 data sets (10 participants x 2 days x 6 trials x 4 repetitions) consisting of 360 sets of success data and 120 sets of failure data. We then split each of the success and failure sets into training sets (70%) and validation sets (30%).

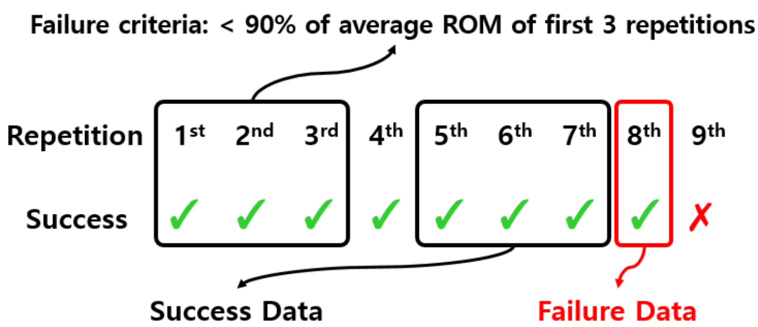

Figure 2: Examples of success and failure data classification

Considering that velocity is a measure of performance and neuromuscular fatigue (García-Ramos et al., 2018), we selected three velocity related features: mean velocity (MV), which is the average velocity in the concentric section; mean propulsive velocity (MPV), which is the average velocity up to the point where the acceleration becomes zero; and peak velocity (PV), which is the maximum velocity (Figure 3). Consulting previous studies (Sanchez-Medina & González-Badillo, 2011; Pareja-Blanco et al., 2017), we also selected MV_{loss} and MPV_{loss}, which are differences in MV and MPV between the current repetition and the previous repetition as additional features. In this study, we used five classification algorithms: linear regression (LR), k-nearest neighbor (KNN), random forest (RF), light gradient boosting (LightGBM), and CatBoost, which are all suitable for binary classification of success and failure (Chen, T., & Guestrin, C., 2016). Then, we compared the accuracy, F1 score, AUC, and response time of the 5 classification algorithms.

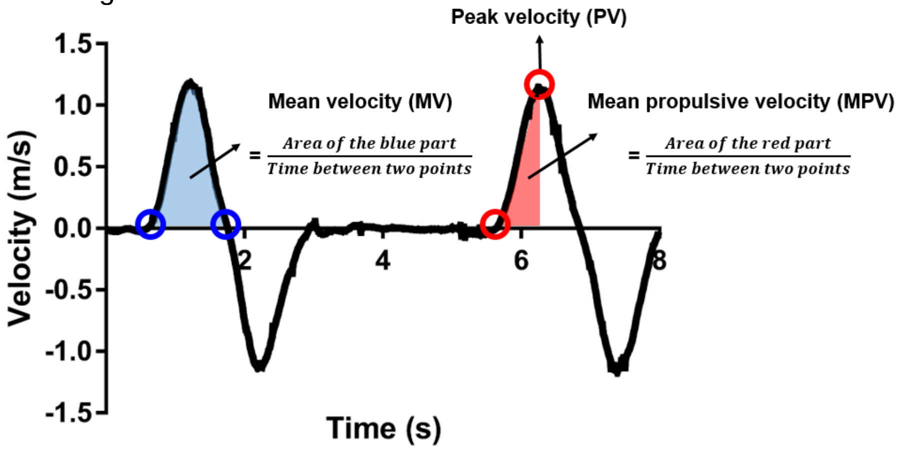

Figure 3: Three velocity related features used in the classification

RESULTS: Table 1 shows the results of model evaluation. Accuracy, precision, recall, F1 score, and receiver operating characteristic (ROC) curve were used for the evaluation (Sokolova et al., 2006). Although the accuracy, recall and F1 score are the highest in CatBoost, this model requires the longest classification time. On the other hand, LR shows sufficiently high accuracy above 0.9, the highest precision and the largest area under the ROC curve (AUC), and requires the shortest classification time.

Table 1: Performance of the machine learning models.

model	Accuracy	Precision	Recall	F1 score	AUC	Response Time
CatBoost	0.9336	0.8612	0.8524	0.8513	0.9054	1.6514
RF	0.9171	0.8184	0.8048	0.8045	0.8856	0.2214
LR	0.9112	0.8810	0.7048	0.7804	0.9171	0.0214
LightGBM	0.9002	0.8150	0.7238	0.7560	0.8737	0.0271
KNN	0.8945	0.8452	0.6571	0.7302	0.8941	0.0229

Figure 4 shows the importance of each feature for the model based on LR. MV has the highest feature importance.

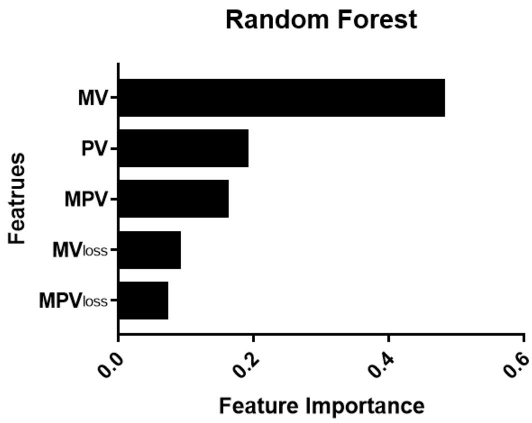

Figure 4: Importance of each feature for the model based on LR

DISCUSSION: We developed 5 failure prediction models and evaluated the performance of each model. Four machine learning models showed accuracy more than 90%, and three of them required classification time less than 0.3 s. In particular, the model based on LR yielded the largest AUC, and the shortest classification time.

In this initial study, we focused on arm curl only. Similar approach can be used to develop other machine learning models that can predict failure point in other types of resistance training.

CONCLUSION: We developed machine learning models that predict the failure point during resistance training with high accuracy and speed. The successful prediction relies on the rapid and significant changes in velocity related variables around the failure point, which is consistent with the results from a previous study that suggested velocity as a reliable indicator of fatigue in resistance training (García-Ramos et al., 2018). To our knowledge, this is the first study that proposes failure point prediction models during resistance training. Embedded with other technologies like wearable devices or smart fitness systems, the proposed models can predict the failure point during resistance training, and send either proper feedback to the trainee or control command to the actuator to enhance the training effects by maintaining proper rate of perceived exertion, and prevent injuries due to excessive training load.

REFERENCES

Davies, T., Orr, R., Halaki, M., & Hackett, D. (2015). Effect of training leading to repetition failure on muscular strength: A systematic review and meta-analysis. *Sports Medicine*, 46(4), 487–502.

Freitas de Salles, B., Simao, R., Miranda, F., da Silva Novaes, J., Lemos, A., & Willardson, J. M. (2009). Rest interval between sets in strength training. *Sports medicine*, *39*(9), 765-777.

García-Ramos, A., Pestaña-Melero, F. L., Pérez-Castilla, A., Rojas, F. J., & Haff, G. G. (2018). Mean velocity vs. mean propulsive velocity vs. peak velocity: which variable determines bench press relative load with higher reliability? *The Journal of Strength & Conditioning Research*, *32*(5), 1273-1279.

Grgic, J., Schoenfeld, B. J., Orazem, J., & Sabol, F. (2022). Effects of resistance training performed to repetition failure or non-failure on muscular strength and hypertrophy: A systematic review and meta-analysis. *Journal of Sport and Health Science*, 11(2), 202–211.

Kerr, Z. Y., Collins, C. L., & Dawn Comstock, R. (2010). Epidemiology of weight training-related injuries presenting to United States Emergency Departments, 1990 to 2007. *The American Journal of Sports Medicine*, 38(4), 765–771.

Kraemer, W. J., Fry, A. C., Ratamess, N., & French, D. (1995). Strength testing: development and evaluation of methodology. *Physiological assessment of human fitness*, *2*, 119-150.

Pareja-Blanco, F., Rodríguez-Rosell, D., Sánchez-Medina, L., Sanchis-Moysi, J., Dorado, C., Mora-Custodio, R., ... & González-Badillo, J. J. (2017). Effects of velocity loss during resistance training on athletic performance, strength gains and muscle adaptations. *Scandinavian journal of medicine & science in sports*, *27*(7), 724-735.

Pearson, D., Faigenbaum, A., Conley, M., & Kraemer, W. J. (2000). The National Strength and Conditioning Association. Basic Guidelines for the resistance training of athletes. *Strength and Conditioning Journal*, 22(4), 14.

Westcott, W. L. (2012). Resistance training is medicine. *Current Sports Medicine Reports*, 11(4), 209–216.

Sanchez-Medina, L., & González-Badillo, J. J. (2011). Velocity loss as an indicator of neuromuscular fatigue during resistance training. *Medicine and science in sports and exercise*, *43*(9), 1725-1734.

Stone, M. H., Chandler, T. J., Conley, M. S., Kramer, J. B., & Stone, M. E. (1996). Training to muscular failure: is it necessary?. *Strength and Conditioning*, *18*, 44-47.

Winett, R. A., & Carpinelli, R. N. (2001). Potential health-related benefits of resistance training. *Preventive Medicine*, 33(5), 503–513.

ACKNOWLEDGEMENTS: This research was supported in part by the Technology Innovation Program (No. 20008912), Industrial Technology Innovation Program (No. 20007058, Development of safe and comfortable human augmentation hybrid robot suit), and Industrial Strategic Technology (No. 20018157) funded by the Ministry of Trade, Industry & Energy (MOTIE, Korea), and National Research Foundation of Korea (NRF) Grants funded by the Korean Government (MSIT) (No. RS-2023-00208052).