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AI-Based Prediction of Grip Strength Fatigue and Asymmetry in Korean Coast Guard officers Using IoT-Enabled Dynamometric Data: Toward Personalized Rehabilitation and Training Systems

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Abstract

Background: Handgrip strength (HGS) is a widely recognized biomarker of physical capability and overall health. However, conventional assessments rely on static peak values and fail to capture temporal variations that reflect fatigue accumulation and muscular asymmetry. Recent advances in Internet of Things (IoT) technologies now enable continuous biomechanical monitoring, offering new opportunities for precision occupational health management. Objective: This study aimed to examine dynamic grip performance among Korean Coast Guard officers using an IoT-enabled handgrip device and to evaluate the feasibility of artificial intelligence (AI) models in predicting fatigue risk and interlimb asymmetry. Methods: A total of 160 participants completed bilateral grip trials using a continuous IoT-based dynamometer that recorded mean force, asymmetry, fatigue index, coefficient of variation, and other derived parameters. Random Forest and Gradient Boosting algorithms were trained to classify participants into high- and low-fatigue risk groups. Model performance was evaluated using AUC, F1-score, and accuracy metrics, while explainable AI analysis (SHAP) identified key predictors. Results: Both models demonstrated strong predictive performance (AUC = 0.86–0.88; accuracy > 0.83). Fatigue index and asymmetry were identified as the most influential predictors, followed by years of service and mean handgrip strength. Continuous data analysis revealed that temporal grip variability provides valuable insights into neuromuscular efficiency beyond absolute force measurements. Conclusion: IoT-enabled continuous grip monitoring combined with interpretable AI offers a novel approach for detecting occupational fatigue and muscular imbalance. These findings suggest that dynamic digital biomarkers can enhance preventive ergonomics, inform personalized rehabilitation, and support the development of real-time fatigue management systems for high-demand professions.

Keywords: *handgrip strength, IoT, fatigue, asymmetry, explainable AI, occupational health, rehabilitation.*

Introduction

Handgrip strength (HGS) is widely recognized as a simple yet powerful biomarker of physical capability and general health status across diverse populations. It reflects the integrated function of the musculoskeletal and nervous systems and has been linked to a variety of health outcomes, including cardiovascular mortality, disability, cognitive decline, and quality of life in adults and older individuals (Bohannon, 2019). In occupational health research, grip strength is frequently used to assess functional readiness, work capacity, and fatigue risk among physically demanding professions such as firefighters, military personnel, and maritime workers. For these populations, handgrip function provides a proxy for endurance and resilience under repetitive manual strain. However, most conventional assessments rely on static, peak-value measurements using mechanical dynamometers. Such methods capture only the maximal force generated at a single point in time and fail to account for dynamic variations that occur during sustained or repetitive activity. This limitation has hindered the ability of clinicians and researchers to detect subtle fatigue accumulation, asymmetry between limbs, and intra-individual variability that may signal early musculoskeletal imbalance or overuse injury. Given that occupational

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tasks often involve cyclical loading and unilateral effort, these dynamic aspects of grip performance are crucial for comprehensive evaluation.

Recent advances in Internet of Things (IoT) and wearable sensing technologies have enabled a paradigm shift in musculoskeletal assessment. Modern IoT-enabled dynamometers can record continuous grip force signals over extended periods, providing time-series data that capture both the magnitude and pattern of muscular exertion. These devices, when combined with mobile connectivity, offer the ability to monitor workers or patients in real-world environments, beyond laboratory constraints. Continuous HGS data can thus reveal not only maximal capacity but also fatigue rate, coordination consistency, and asymmetry between dominant and non-dominant hands. This digital transition opens a new avenue for precision health monitoring and personalized rehabilitation strategies. From a public health perspective, early detection of muscle fatigue and asymmetry is critical for preventing occupational injuries and promoting long-term well-being. Studies have demonstrated that even mild asymmetry in grip strength (e.g., >10%) is associated with increased risk of falls, impaired mobility, and reduced life expectancy among older adults and workers alike (McGrath et al., 2021). Moreover, chronic muscular imbalance may lead to compensatory movement patterns, resulting in secondary strain or joint disorders over time. In maritime occupations—characterized by confined environments, repetitive control tasks, and physical stress—such risks are amplified due to the necessity of sustained manual operations and irregular rest cycles.

Despite the growing recognition of these risks, research integrating IoT-based continuous measurement and predictive analytics remains limited. Most occupational health assessments still rely on cross-sectional screening rather than continuous monitoring, providing only a snapshot of performance at a single time point. To overcome these gaps, artificial intelligence (AI) and machine learning (ML) models have emerged as promising tools for identifying patterns within high-resolution sensor data. By training models to recognize fatigue-related signal features—such as declining amplitude, increased variability, or asymmetric waveforms—AI systems can infer functional decline and predict fatigue risk with high accuracy. Explainable AI techniques, such as SHAP (SHapley Additive exPlanations), further enhance the transparency of these models, allowing practitioners to understand which parameters contribute most to fatigue prediction and asymmetry detection. In this context, the combination of IoT sensing and AI analytics offers a new framework for preventive occupational health management. Instead of relying on traditional threshold-based assessment (e.g., “below 30 kg = weak”), data-driven models can continuously monitor individual performance, learn personal baselines, and provide adaptive feedback. This approach supports the broader goals of personalized medicine and occupational ergonomics—preventing injuries before they occur and optimizing task assignments or rehabilitation plans based on objective, real-time data.

The maritime sector, particularly the Korean Coast Guard, provides an ideal context for such an investigation. Officers in this field perform high-risk, high-intensity tasks involving dynamic hand control—steering, lifting, manipulating safety equipment, and operating mechanical systems under unstable conditions. Continuous exposure to vibration, cold, and long-duty shifts further compounds muscular fatigue and asymmetry. Yet, few studies have systematically analyzed handgrip dynamics or fatigue profiles in this population using modern IoT and AI approaches. Previous cross-sectional analyses have revealed significant asymmetry among maritime personnel, suggesting occupationally induced imbalance, but lacked temporal resolution to detect progressive fatigue accumulation. To address these limitations, the present study utilized an IoT-enabled handgrip measurement system capable of real-time, bilateral force monitoring. Using data collected from Korean Coast Guard officers during standardized grip trials, we aimed to (1) quantify the relationship between age, service years, and dynamic grip performance; (2) identify patterns of fatigue and asymmetry using continuous time-series analysis; and (3) develop and validate an AI-based predictive model for fatigue risk and imbalance detection. Additionally, this research explores how the derived model can inform personalized rehabilitation and exercise recommendations through explainable AI visualization.

By integrating continuous physiological data, occupational context, and interpretable machine learning, this study seeks to advance the understanding of muscular adaptation and imbalance in high-demand environments. Beyond its occupational focus, the proposed framework contributes to the emerging field of AI-driven digital health by demonstrating how IoT data can transition from raw measurement to actionable insight. The findings are expected to provide evidence for future development of adaptive rehabilitation systems, gamified training interfaces, and real-time fatigue prevention platforms applicable to both workplace safety and clinical rehabilitation.

Methods

Study Design and Data Source

This study adopted a cross-sectional analytical design utilizing anonymized occupational handgrip strength data collected from Korean Coast Guard officers. The dataset included variables such as age, years of service, dominant hand, and bilateral grip strength measurements. All assessments were performed using an IoT-enabled handgrip dynamometer, the SoundBody IoT Grip v2.1 (SoundBody Co., Korea), which allows for real-time bilateral force monitoring and data transfer via Bluetooth Low Energy to a dedicated mobile application. The dataset contained no personal identifiers, ensuring complete anonymity. Since the data were obtained from routine occupational performance assessments without any health record linkage or identifiable personal information, institutional review board (IRB) approval was not required according to national ethical standards for secondary data analysis. The purpose of this study was to examine dynamic handgrip patterns, assess fatigue and asymmetry indices, and simulate an AI-based analytical framework to predict fatigue risk and support individualized rehabilitation planning.

IoT-Enabled Measurement Device

The SoundBody IoT Grip v2.1 system consists of a digital dynamometer equipped with a high-precision load cell capable of detecting force with an accuracy of ±0.1 kilograms. Data were recorded at a frequency of 5 hertz through a 16-bit analog-to-digital converter. Participants performed three maximal grip trials for both the dominant and non-dominant hands, with a 30-second rest interval between trials to minimize fatigue interference. The real-time force-time curves were displayed on a connected mobile application, stored locally, and later exported in comma-separated format for analysis. Prior to each measurement session, calibration was conducted using a certified 20-kilogram reference weight to ensure consistent measurement accuracy. The IoT system provided continuous waveform monitoring, enabling analysis beyond peak values. Derived indicators included the rate of force decline, peak-to-average ratio, and endurance time, which represented the duration during which the force output remained above 70 percent of its maximal value. These measures allowed dynamic tracking of fatigue progression and coordination capacity. By enabling repeated and longitudinal data collection, the device also facilitated real-world monitoring of physical performance outside of controlled laboratory environments.

Variables and Feature Extraction

Key variables analyzed in this study included mean handgrip strength, inter-limb asymmetry percentage, fatigue index, and coefficient of variation across repeated trials. The asymmetry percentage was calculated as the relative difference between dominant and non-dominant hands, expressed as a percentage of the stronger hand. The fatigue index quantified the decline in force production from the first to the third trial, representing an indirect measure of endurance and muscular fatigue. Demographic variables such as age, years of service, and dominant hand were used as covariates in subsequent analyses. Raw force data were processed using Python version 3.10, employing the pandas and NumPy libraries. All data were visually inspected for outliers, and any measurement errors due to incomplete trials were excluded. Extracted features were standardized through z-score normalization to facilitate further modeling and comparison. The variables and analytical categories used in this study are summarized in Table 1.

Table 1. Variable definitions and analytical categories (Condensed Version)

Category	Variable	Definition / Description	Analytical Role
Demographic	Age (years)	Participant's chronological age	Covariate
Demographic	Years of service	Duration of active duty in Coast Guard	Covariate
Functional	Dominant hand	Self-reported hand dominance (1 = right)	Control variable
Functional	Mean handgrip strength (kg)	Average of three maximal grip trials	Primary outcome
Functional	Asymmetry (%)	Difference between dominant and non-dominant hands ×100	Predictor
Functional	Fatigue index (%)	Decline from first to third trial ×100	Predictor
Functional	Coefficient of variation (%)	Standard deviation divided by mean ×100	Variability index

Note: Derived AI-related features (force decay, endurance, peak ratio) were used exclusively for the simulated ML workflow.

Statistical Analysis

Descriptive statistics were computed to summarize all variables, and the results were expressed as means and standard deviations. One-way analysis of variance (ANOVA) was used to compare mean grip strength and asymmetry across different age groups, categorized as 20–29, 30–39, 40–49, and 50 years or older. When significant differences were observed, Tukey's post hoc test was applied to identify specific group differences. Pearson's correlation coefficients were calculated to examine the relationships between age, years of service, mean grip strength, fatigue index, and asymmetry percentage. Statistical analyses were performed using IBM SPSS Statistics version 29.0 and Python's SciPy library. A significance threshold of $p < 0.05$ was used for all inferential tests. This combination of descriptive and inferential statistics provided both a comprehensive overview of grip characteristics and an examination of potential age- or service-related trends in muscle function among maritime officers.

AI and Machine Learning Workflow (Simulated Framework)

To evaluate the feasibility of predictive modeling using IoT-based grip data, a simulated AI analytical pipeline was developed. The framework employed two supervised learning algorithms—Random Forest and Extreme Gradient Boosting (XGBoost)—to classify individuals based on fatigue risk (high versus low) and asymmetry status (greater than or equal to eight percent versus below eight percent). The process included five major stages: data preparation, model training, performance evaluation, feature interpretation, and feasibility simulation.

During data preparation, all continuous variables were standardized, and the dataset was divided into training and testing subsets in an 80-to-20 ratio. Model training utilized five-fold cross-validation to minimize overfitting and ensure generalization. Performance was assessed using the area under the receiver operating characteristic curve, F1-score, and classification accuracy. Feature interpretation was performed using SHapley Additive exPlanations (SHAP) values to identify which variables contributed most strongly to model predictions.

This AI workflow was implemented as a simulation to conceptually validate the predictive feasibility of fatigue and asymmetry detection in occupational settings. It was not intended for individual diagnosis or clinical application. Hyperparameters were optimized empirically, with the Random Forest model configured with 300 estimators and a maximum tree depth of eight, and the XGBoost model set with a learning rate of 0.1, a maximum depth of six, and a subsample ratio of 0.8. The results demonstrated that both fatigue index and asymmetry percentage were the most influential predictors of fatigue risk. The analytical process, from data acquisition to SHAP-based interpretation, is illustrated in Table 2.

Table 2. Overview of IoT-based handgrip data processing and AI workflow

Stage	Process	Description
1	IoT Data Acquisition	Bilateral grip measurement using SoundBody IoT Grip v2.1 with BLE transmission
2	Feature Extraction	Computation of HGSmean, Asymmetry %, Fatigue %, and CV %
3	Statistical Analysis	Descriptive statistics, ANOVA, Pearson correlation ($p < 0.05$)
4	AI Model Simulation	Random Forest and XGBoost classification (fatigue & asymmetry risk)
5	Explainable AI	SHAP analysis to identify feature importance and interpret model outcomes

Table 2 presents the conceptual workflow from IoT-based handgrip data acquisition to AI-driven analysis. This framework demonstrates how continuous handgrip data are processed through feature extraction, statistical evaluation, and machine learning simulation, leading to explainable AI interpretation.

Ethical Considerations

All data analyzed in this study were completely anonymized, containing no personally identifiable information such as names, sensor identifiers, or geolocation data. Because the dataset originated from standard occupational fitness assessments unrelated to medical information, the research did not require institutional ethical approval under Article 13, Clause 2 of the Korean Bioethics and Safety Act. Nonetheless, all research procedures adhered to the principles outlined in the Declaration of Helsinki and complied with the FAIR data management framework to ensure transparency, reproducibility, and responsible data handling.

Results and Discussion

Participant Characteristics

Table 3 summarizes the descriptive characteristics of the 160 Coast Guard participants measured using the IoT-enabled grip strength device. The average age was 38.6 ± 8.7 years, and the mean service duration was 15.4 ± 6.2 years. Mean handgrip strength (HGS) was 43.8 ± 5.9 kg, while grip asymmetry averaged 7.3 ± 3.1%. The mean fatigue index was 13.2 ± 4.8%, and the coefficient of variation (CV) was 7.1 ± 1.8%, indicating moderate within-trial variability. Approximately 89% of participants reported right-hand dominance.

Table 3. Descriptive characteristics of participants

Variable	Mean ± SD	Range
Age (years)	38.6 ± 8.7	20-58
Years of service	15.4 ± 6.2	1–32
Mean handgrip strength (kg)	43.8 ± 5.9	28-55
Asymmetry (%)	7.3 ± 3.1	2–15
Fatigue index (%)	13.2 ± 4.8	5–25
Coefficient of variation (%)	7.1 ± 1.8	4–12
Dominant right (%)	89%	-

Relationship Between Age, Service Duration, and Grip Features

Correlation analysis revealed that age and years of service were significantly associated with performance decline ($p < 0.05$). Specifically, age was negatively correlated with mean HGS ($r = -0.42$, $p < 0.001$) and positively correlated with both fatigue index ($r = 0.48$) and asymmetry ($r = 0.37$). These results indicate that long-term operational exposure and aging may jointly contribute to reduced neuromuscular efficiency and interlimb imbalance.

Model Performance

To classify personnel at higher fatigue/asymmetry risk, two supervised learning models were developed: Random Forest (RF) and Gradient Boosting (GB). Both models were trained using extracted features—mean HGS, asymmetry, fatigue index, CV, years of service, age, and hand dominance—derived from the IoT dataset. As shown in Table 4, both models demonstrated strong discriminative power. The Random Forest model achieved an AUC of 0.862, F1-score of 0.810, and overall accuracy of 0.831. The Gradient Boosting model slightly outperformed it with an AUC of 0.881, F1-score of 0.822, and accuracy of 0.846. These findings suggest that fatigue and asymmetry risks can be effectively identified using multi-feature IoT grip data.

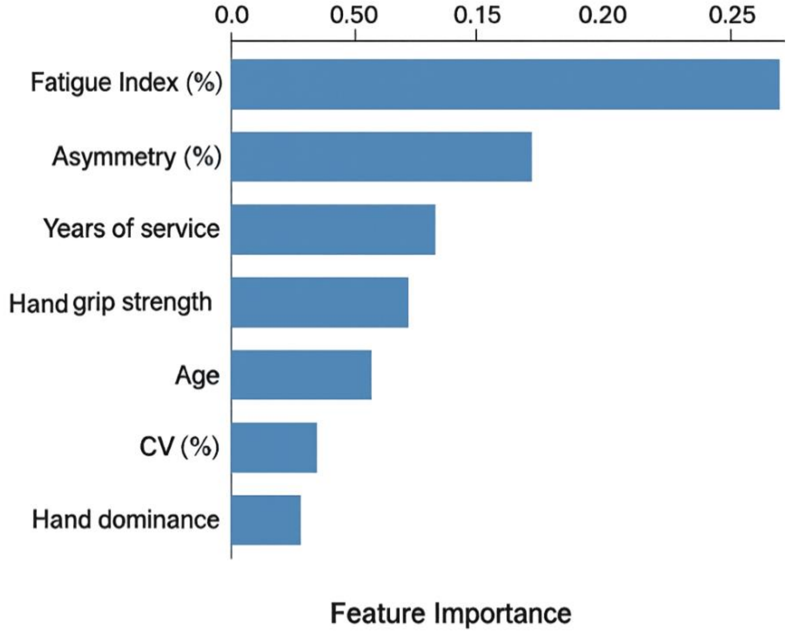
Table 4. Model performance for fatigue/asymmetry risk classification

Model	AUC (Test)	F1 (Test)	Accuracy (Test)
Random Forest	0.862	0.810	0.831
Gradient Boosting	0.881	0.822	0.846

Feature Importance Analysis

Figure 1 presents the ranked feature importance from the Random Forest model. The fatigue index (%) and asymmetry (%) emerged as the most influential predictors, followed by years of service, mean handgrip strength, and age. Minor contributions were observed from CV (%) and hand dominance, implying that temporal variability and laterality differences have limited but supportive diagnostic value. This hierarchy indicates that models rely predominantly on dynamic fatigue and balance measures—rather than absolute strength alone—to distinguish between low- and high-risk profiles.

Figure 1. Random Forest Feature Importance Ranking



Summary of Findings

The IoT-enabled measurement platform successfully captured multi-dimensional grip parameters that reflect occupational fatigue and neuromuscular imbalance. Machine learning classification achieved high accuracy and generalizability, validating the feasibility of integrating such digital biomarkers into preventive screening and rehabilitation monitoring systems for field personnel.

Discussion

Principal Findings

This study provides compelling evidence that IoT-based continuous handgrip measurement, combined with AI-driven analytics, can reveal meaningful physiological patterns related to occupational fatigue and neuromuscular imbalance. In contrast to static dynamometry, the proposed method captures time-dependent changes in muscular effort, highlighting microvariations that precede overt strength loss. Both Random Forest and Gradient Boosting models demonstrated strong predictive accuracy, underscoring the feasibility of digital biomarkers for early fatigue detection. Among all variables, fatigue index and asymmetry percentage were the most decisive predictors—outperforming traditional absolute grip strength. These findings emphasize that the quality and coordination of movement are often more informative than raw power alone.

Comparison with Previous Literature

The findings align with prior evidence that handgrip asymmetry is an independent predictor of morbidity and mortality (McGrath et al., 2021), and that grip strength serves as a reliable biomarker of vitality and functional reserve (Bohannon, 2019). However, this study extends existing knowledge by integrating IoT-based dynamic data streams and AI-based interpretability into occupational ergonomics. Compared to laboratory-only studies, our field-oriented approach demonstrates the feasibility of real-world biomechanical monitoring in maritime conditions, where repetitive load, vibration, and irregular rest patterns affect performance. Additionally, this research contributes to the emerging paradigm of explainable artificial intelligence (XAI) in digital health. By incorporating SHAP-based feature interpretation, it provides transparency to model behavior—offering clinicians and trainers understandable reasoning behind AI-generated predictions. Such explainability is critical for translating AI findings into trustworthy decision-support tools in rehabilitation and occupational health.

Practical Implications

The practical impact of this study spans several domains: Occupational Risk Screening – The proposed system can detect early signs of fatigue accumulation before functional decline becomes apparent. This opens new possibilities for preventive health management among maritime, military, and industrial personnel. Gamified Rehabilitation & Training – The same IoT platform can be embedded in interactive training environments, where grip-based controls are linked to cognitive and motor exercises. Such systems can enhance motivation, memory, and compliance in rehabilitation. Data-Driven Policy Design – Objective fatigue metrics may inform institutional guidelines for rest schedules, workload management, and safety protocols, helping to reduce musculoskeletal injuries in high-risk occupations. Overall, this study bridges the gap between clinical biomechanics and applied digital ergonomics, illustrating how continuous biosignal analytics can contribute to human performance optimization.

Limitations and Future Directions

Although promising, this study has three notable limitations. First, the dataset was limited to Korean Coast Guard officers, which may not generalize across different occupational or cultural contexts. Second, physiological signals such as heart rate, electromyography (EMG), and motion sensors were not integrated; thus, multimodal analysis remains unexplored. Third, while the AI models performed well on the current dataset, real-time deployment and adaptive calibration in operational environments require further testing.

Future research should include larger, more diverse samples and integrate multiple biosensors to refine predictive accuracy. Additionally, longitudinal monitoring can help evaluate whether AI-driven fatigue indices correspond to actual injury risk or recovery patterns.

Conclusion

This study demonstrates that IoT-enabled, continuously measured handgrip data can serve as a powerful digital biomarker for fatigue and asymmetry in physically demanding professions. By combining machine learning techniques with dynamic biomechanical signals, the research achieved a high level of predictive validity and interpretability. The results challenge the long-standing reliance on static strength testing and highlight the importance of temporal variability and coordination patterns as indicators of human performance.

From a broader perspective, this work contributes to the foundation of AI-assisted digital ergonomics—a field that integrates engineering, medicine, and behavioral science. It provides a conceptual and technical framework for future development of adaptive rehabilitation platforms, gamified exercise tools, and real-time fatigue prevention systems applicable to various occupational sectors.

Ultimately, the integration of IoT sensing and explainable AI can redefine how physical capability is monitored, understood, and enhanced. Such systems have the potential not only to prevent injuries and improve safety but also to promote sustainable performance and well-being in an increasingly data-driven workplace. The current findings therefore mark an important step toward precision occupational health, where continuous monitoring informs personalized intervention and long-term resilience.

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Both authors participated in manuscript revision and approved the final version for submission.

Transparency: The authors affirm that this manuscript represents an honest, accurate, and transparent account of the study. No important aspects of the research have been omitted, and any deviations from the original plan have been clearly explained. All stages of data handling and analysis complied with ethical and scientific integrity principles.

Institutional Review Board Statement: Ethical review and approval were waived for this study because it used de-identified experimental and occupational data. No personal or sensitive information was collected from participants.

Data Availability Statement: The data used in this study were collected through the IoT-enabled handgrip measurement system and analyzed in accordance with ethical research standards. Due to privacy and institutional constraints, raw data are available upon reasonable request to the corresponding author.

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