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Sarcopenia classification model for musculoskeletal patients using smart insole and artificial intelligence gait analysis

Shinjune Kim[1], Hyeon Su Kim[1] & Jun-Il Yoo[2]*

[1]*Department of Biomedical Research Institute, Inha University Hospital, Incheon, South Korea;* [2]*Department of Orthopaedic Surgery, Inha University Hospital, Incheon, South Korea*

Abstract

Background The relationship between physical function, musculoskeletal disorders and sarcopenia is intricate. Current physical function tests, such as the gait speed test and the chair stand test, have limitations in eliminating subjective influences. To overcome this, smart devices utilizing inertial measurement unit sensors and artificial intelligence (AI)-based methods are being developed.

Methods We employed cutting-edge technologies, including the smart insole device and pose estimation based on AI, along with three classification models: random forest (RF), support vector machine and artificial neural network, to classify control and sarcopenia groups. Patient data of 83 individuals were divided into train and test sets, with approximately 67% allocated for training. Classification models were implemented using RStudio, considering individual and combined variables obtained through pose estimation and smart insole measurements.

Results Performance evaluation of the classification models utilized accuracy, precision, recall and F1-score indicators. Using only pose estimation variables, accuracy ranged from 0.92 to 0.96, with F1-scores of 0.94–0.97. Key variables identified by the RF model were 'Hip_dif', 'Ankle_dif' and 'Hipankle_dif'. Combining variables from both methods increased accuracy to 0.80–1.00, with F1-scores of 0.73–1.00.

Conclusions In our study, a classification model that integrates smart insole and pose estimation technology was assessed. The RF model showed impressive results, particularly in the case of the Hip and Ankle variables. The growth of advanced measurement technologies suggests a promising avenue for identifying and utilizing additional digital biomarkers in the management of various disorders. The convergence of AI technologies with diagnostics and treatment approaches a promising future for enhanced interventions in conditions like sarcopenia.

Keywords classification model; musculoskeletal disorders; pose estimation; sarcopenia; smart insole

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**Correspondence to: Jun-Il Yoo, Department of Orthopaedic Surgery, Inha University Hospital, 27, Inhang-ro, Jung-gu, Incheon, South Korea. Email: furim@hanmail.net*

Introduction

Sarcopenia is a condition in which muscle strength, function and skeletal mass gradually deteriorate as a result of aging, lack of exercise, poor nutrition and chronic illness.[1,2] The definition of sarcopenia varies across different global institutions, including the European Working Group on Sarcopenia in Older People (EWGSOP), the International Working Group on Sarcopenia (IWGS) and the Asian Working Group for Sarcopenia (AWGS). Among these, the representative institution, EWGSOP, characterizes sarcopenia as a progressive and general skeletal muscle disorder.[2–4] Although each institution's definition of sarcopenia differs slightly, it is common that it results in muscle mass and physical performance loss

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and suggests that it can lead to serious health problems if appropriate treatment is not provided.[5,6]

Maintaining musculoskeletal health is heavily reliant on physical function, which is determined by a blend of strength, endurance, power and coordination. Besides sarcopenia, abnormal muscle function can lead to a diverse array of musculoskeletal disorders (MSDs), ranging from acute injuries like fractures and sprains to chronic ailments like rheumatoid arthritis and osteoarthritis (OA).[7]

The relationship between physical function, MSDs and sarcopenia is complex and multifaceted. Currently, various tests are conducted to assess physical function and identify potential issues with MSDs and sarcopenia at an early stage. These tests include the gait speed test, the chair stand test and the timed up and go test.[8,9] However, these methods have limitations as they may be influenced by the measurer's subjectivity and individual patient variability.[10] To overcome these limitations, research is currently underway to develop smart devices that utilize inertial measurement unit (IMU) sensors, pressure sensors and artificial intelligence (AI)-based measurement methods for extracting patients' pattern data in their daily lives.[10–12] Smart insoles that utilize pressure sensors and IMU are widely utilized for measuring patients with MSDs, including those with sarcopenia. They are particularly valuable for fall detection, movement monitoring and balance assessment. Additionally, the pose estimation method is extensively employed in gait analysis and sports fields.[13,14] Pose estimation is an advanced computer vision technology that employs deep learning models to accurately estimate key points of the human body in real time.[15] By tracking and detecting the joints and parts of the body, it enables precise 2D or 3D pose estimation.[16,17] Currently, ongoing research endeavours are focused on comparing the accuracy and effectiveness of pose estimation with the VICON motion system (Vicon Nexus; Vicon Motion Systems Ltd., Oxford, England), renowned for its utilization of multiple cameras for highly precise 3D motion capture.[18,19] As AI analysis techniques continue to advance, the domain of medical research actively explores the evaluation of physical function, including the pursuit of accurate body position tracking.[10,11] These advancements hold great potential for improving our understanding of human movement and enhancing the assessment and treatment of various medical conditions.

Therefore, the objective of this study is two-fold. First, we aim to investigate the effectiveness of pose estimation and smart insole in accurately measuring the gait pattern of sarcopenia patients. By utilizing these advanced technologies, we can capture comprehensive data on joint movements, angles and speeds, providing valuable insights into their physical activity patterns. Second, our goal is to develop a robust prediction model using supervised learning methods and gait analysis data, differentiating between MSD patients with sarcopenia (sarcopenia group) and without sarcopenia (control group). By incorporating the cutting-edge technologies of pose estimation and smart insole, we can enhance the accuracy and efficiency of the classification model, paving the way for improved diagnosis and treatment of sarcopenia.

Materials and methods

Participants

In 2022, our study included 83 patients diagnosed with MSDs who were capable of walking at Gyeongsang National University Hospital (GNUH) in Jinju, South Korea. Among these 83 patients, 43 had hip-related issues, 33 had femur-related issues and 11 had issues related to other areas. There were four instances of overlapping regions between the two categories. Among the 43 individuals with hip-related conditions, fractures were observed 18 times, OA occurred 14 times and avascular necrosis (AVN) appeared 13 times, with other cases totalling 38. For femur-related issues, there were 30 cases of fractures and 21 cases of other conditions. Among non-hip and non-femur cases, fractures were observed 4 times, AVN occurred 3 times and other conditions were noted 10 times.

Various assessments were conducted on the patients, encompassing measurements of grip strength, walking speed, dual-energy X-ray absorptiometry (DXA) and other metrics. To delve into specifics, for muscle mass, DXA was employed. The criteria utilized were <7.0 kg/m^2 for males and <5.4 kg/m^2 for females. Concerning muscle strength, grip strength standards were set at <28 kg for males and <18 kg for females. As for physical performance, the classification criterion involved a 6-m walking speed test with a threshold of <1.0 m/s. These criteria for classifying sarcopenia were drawn from the 2019 guidelines of the AWGS.[3] Based on these criteria, among the 83 patients with MSDs, 23 patients were pre-classified as individuals with sarcopenia. Out of the 23 patients diagnosed with sarcopenia, 15 were female and 8 were male (refer to *Table 1*).

In contrast, among the 60 patients who did not have sarcopenia, 29 were female and 31 were male. The average age of the non-sarcopenia group was 63.4 years (SD: 15.4), with an average height of 162.7 cm (SD: 9.1) and an average weight of 63.7 kg (SD: 13.2).

The study adhered to the principles outlined in the Declaration of Helsinki and received approval from the institutional review board at GNUH. All research procedures were conducted in strict compliance with ethical standards, ensuring the protection of participants' privacy, confidentiality and rights.

Pose estimation method

The study utilized a smartphone (Galaxy A20, Samsung Electronics) to collect video data for pose estimation. The measurements were obtained using the smartphone's rear

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Table 1 Characteristics of the sarcopenia and control groups

	Sarcopenia				Control			
	Sex	Age (SD)	Height (SD)	Weight (SD)	Sex	Age (SD)	Height (SD)	Weight (SD)
Female	15	77.5 (9.3)	153.0 (5.6)	50.1 (7.2)	29	69.0 (16.5)	155.4 (5.9)	55.2 (10.8)
Male	8	78.4 (7.5)	168.2 (8.3)	63.5 (8.1)	31	58.1 (12.4)	169.5 (5.6)	71.7 (9.9)
Total	23	77.8 (8.6)	158.3 (9.9)	54.8 (9.8)	60	63.4 (15.4)	162.7 (9.1)	63.7 (13.2)

Note: Sex, *n*; age, years; height, cm; weight, kg.

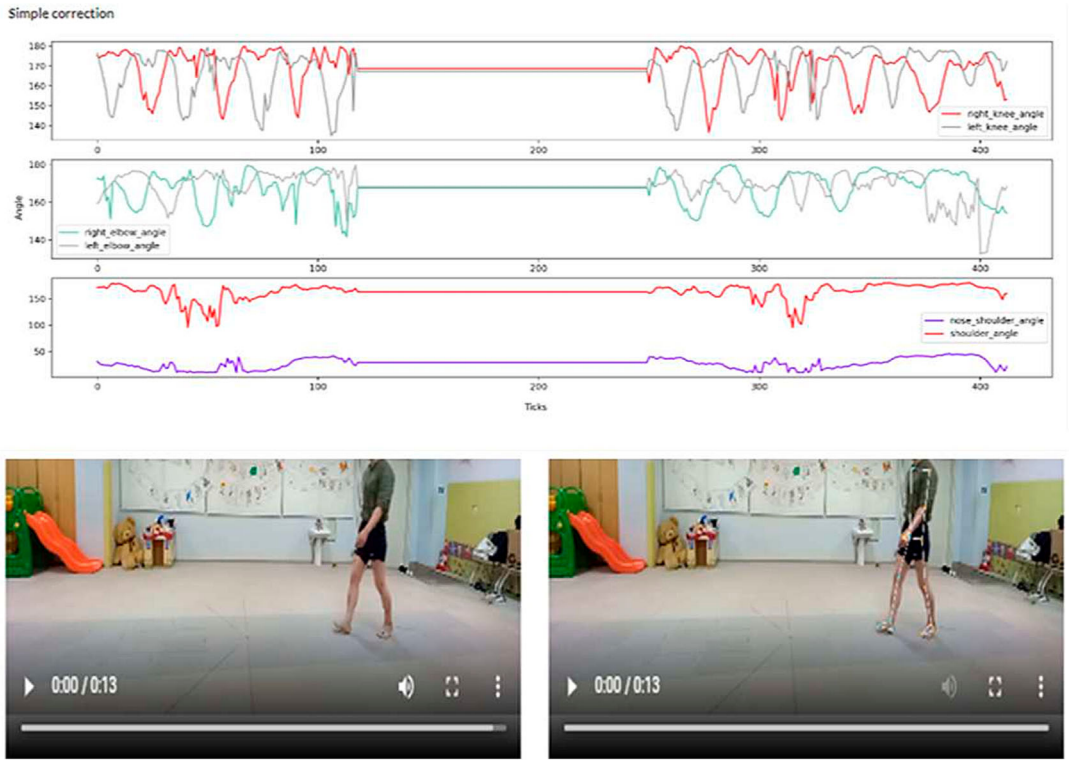

Figure 1 Gait information obtained through open pose estimation.

camera, maintaining a recording resolution of 1080 p and a frame rate of 30 fps. The video recording procedure involved capturing a side view video of one round trip for a 5-m walking distance. As there were no standardized measurement distances and heights available, the distance between the patients and the camera was set at a vertical distance of 2 m from the floor, with a height of 1.3 m as the reference point. The 2-m interval was chosen as the minimum distance required to encompass the 5-m walking distance. Additionally, maintaining the height at approximately 1.3 m, which is the height of a person's shoulder, ensured horizontal alignment with the ground and accounted for any angle or horizontal deviations. For video analysis, the study utilized the MediaPipe software, which is based on a convolutional neural network model.[20] Specifically, the BlazePose algorithm within MediaPipe, developed by Google, was employed to track 33 key points that represent major joints in real time.[21] This algorithm incorporates a total of 11 facial key points, along with 22 key points distributed across the body: 2 on each shoulder, 2 on each elbow, 2 on each wrist, 6 on the fingers, 2 on each hip, 2 on each knee, 2 on each ankle, 2 on each heel and 2 on each toe, symmetrically positioned on both the left and right sides. The DEEVO Data Management System (DEEVO, Jinju, South Korea) was used for estimating the key points and storing the collected video data (refer to *Figure 1*).[22] Furthermore, the Dr.log application (DEEVO) was utilized to extract 23 variables representing the angles of each joint and the positional differences between joint locations based on the estimated 33 key points.

Smart insole method

To assess the gait pattern of the 83 patients, SALTED (Seoul, South Korea) smart insoles were utilized to collect movement information data.[23] These smart insoles consist of four

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pressure sensors and one 3-axis IMU sensor. As depicted in *Figure 2*, three pressure sensors are positioned at the front and one at the heel, while the IMU sensor is integrated into a board connected to the pressure sensors, located at the centre of the insole. The pressure sensors detect the pressure at each point to determine ground contact and the centre of pressure. The IMU sensor uses acceleration and gyroscope values to capture foot movement. This allowed for the extraction of data related to foot pressure and acceleration, which were wirelessly transmitted in four-channel and three-channel formats, respectively, at a sampling rate of 30 Hz.[23] To capture the patient's natural gait, the insole data were collected during a comfortable 1-min walk, without any constraints on walking speed or distance. The walking path covered an indoor distance of 10 m, incorporating straight stretches along with turns at both the starting and ending points. These turns consisted of a right turn at the ending point and a left turn at the starting point. During this period, the collected pressure data were calibrated using the IMU sensor, and subsequent analysis was performed utilizing the internal programme of the SALTED system (refer to *Figure 3*). The analysis of the pressure data led to the extraction of eight variables, which corresponded to the ratios of single support, double support, stance and swing for each foot.

Statistical analysis

To classify the control group and the sarcopenia group, we utilized three representative classification models: random forest (RF), support vector machine (SVM) and artificial neural network (ANN).[24–26] The RF method is an ensemble learning method based on decision trees, while SVM finds a hyperplane to classify data and has shown better performance in classifying binary data compared with decision tree and ANN methods.[27] In this study, we utilized a non-linear algorithm for SVM classification.[28] Lastly, ANN represents a network of neurons with a multi-layer perceptron consisting of multiple hidden layers between an input layer and an output layer.[26] We used ANN classification with only one hidden layer for simplicity of comparison.

To validate each model, the patient data of 83 individuals were divided into a train set and a test set. In order to address the issue of a limited number of samples for sarcopenia patients, approximately 67% of the total data were allocated to the train set, while the remaining approximately 33% were assigned to the test set. Random sampling using random numbers was employed to allocate the data during this process. The sampling technique and classification models utilized were conducted using the RStudio programme.

For both the control group and the sarcopenia group, three classification models were applied to individual variables and combined variables. The first case involved performing classification solely based on variables obtained through pose estimation. The second case focused on classification using variables obtained solely through smart insole. Lastly, classification was performed using a combination of variables obtained through both pose estimation and smart insole, leveraging the two measurement methods.

Figure 2 Layout of the smart insole pressure and inertial measurement unit sensors.

Performance metric

After applying three classification models to individual and combined variables for both the control group and the sarcopenia group, we evaluated their performance using four key performance indicators: accuracy, precision, recall and the F1-score. Accuracy represents the percentage of correctly classified cases (both true positives and true negatives) out of the total number of cases. In the context of classifying sarcopenia and non-sarcopenia, accuracy indicates how well the model can correctly classify both types of patients. Precision, also known as positive predictive value, measures the proportion of true positive cases (correctly identified sarcopenia patients) out of all predicted positive cases (both true positive and false positive). A high precision value means that the model has a low rate of false positives, indicating that when the model predicts a patient to have sarcopenia, the prediction is usually correct. Recall, also known as sensitivity or true positive rate, measures the proportion of true positive cases (correctly identified sarcopenia patients) out of all actual positive cases (both true positive and false negative). In the context of sarcopenia classification, recall shows how well the model can identify actual sarcopenia patients among all the sarcopenia cases. The F1-score is the harmonic mean of precision and recall. In the context of sarcopenia classifica-

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Figure 3 Gait information obtained through smart insole.

tion, the F1-score provides a comprehensive evaluation of the model's performance in correctly identifying both sarcopenia and non-sarcopenia cases. Furthermore, we used the MeanDecreaseGini coefficient, which calculates variable importance based on the decrease in Gini impurity, to rank the importance of variables. This was performed to facilitate variable selection using the interpretable RF model.

Results

The performance metrics for each approach (pose estimation, smart insole and the combination of pose estimation and smart insole) and for each model (RF, SVM and ANN) can be found in *Table 2*. For the smart insole, we provide 8 variables corresponding to support, swing and stance for each foot, while for pose estimation, 23 joint angles and specific details are presented. These details can be found in *Table S1*.

First, when classifying 25 patients into the sarcopenia and control groups using only the pose estimation outcome variable, the three classification models obtained accuracy rates of 0.96 (RF), 0.96 (SVM) and 0.92 (ANN). These results demonstrate their effectiveness in accurately distinguishing between patients with sarcopenia and non-sarcopenia. Furthermore, the F1-score values for each classification model were 0.97 (RF), 0.97 (SVM) and 0.94 (ANN), indicating high performance even in classifying patients with sarcopenia. As seen in *Table 2*, the accuracy and F1-score rates exceeding 0.9 for all three models signified a very high rate of accurate classification. The RF model identified 'Hip_dif', 'Ankle_dif' and 'Hipankle_dif' as key variables based on the MeanDecreaseGini value, clearly standing out from the others with values of 3.590, 3.008 and 2.414, respectively, as depicted in *Table 3* and *Figure 4*.[29] Here, 'Hip_dif' refers to the change in hip angle from the standing position before walk initiation to the maximum angle during walking. Similarly, 'Ankle_dif' signifies the comparable change in the ankle. Finally, 'Hipankle_dif' combines the changes from both these angles.

Second, when using only the smart insole outcome variable for classification, the three models achieved accuracy rates of 0.72 (RF), 0.68 (SVM) and 0.44 (ANN). The corresponding F1-scores were 0.22 (RF), 0.00 (SVM) and 0.34

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Table 2 Performance measures of classification models

Random forest		Sensitivity	Specificity	F1-score	Accuracy
Models	Pose estimation	1.00	0.94	0.97	0.96
	Smart insole	0.12	1.00	0.22	0.72
	Pose estimation and insole	1.00	1.00	1.00	1.00
Support vector machine		**Sensitivity**	**Specificity**	**F1-score**	**Accuracy**
Models	Pose estimation	1.00	0.94	0.97	0.96
	Smart insole	0.00	1.00	0.00	0.68
	Pose estimation and insole	0.62	0.88	0.73	0.80
Artificial neural network		**Sensitivity**	**Specificity**	**F1-score**	**Accuracy**
Models	Pose estimation	1.00	0.88	0.94	0.92
	Smart insole	0.25	0.53	0.34	0.44
	Pose estimation and insole	1.00	0.94	0.97	0.96

Table 3 MeanDecreaseGini value obtained from the random forest method for each classification model

Pose estimation		Smart insole		Pose estimation and smart insole	
Variable	Value	Variable	Value	Variable	Value
hip_dif	3.590	Left_Single_Support	2.508	hip_dif	3.394
ankle_dif	3.008			hipankle_dif	3.354
hipankle_dif	2.414			ankle_dif	2.607
ankle_mean	1.772	Right_Stance	2.494	ankle_mean	1.450
kneeankle_dif	1.540			kneeankle_dif	1.277
shoulder_angle_mean	1.017			shoulder_angle_mean	1.030
knee_max	0.730	Right_DoubleSupport	2.473	hip_mean	0.911
ankle_max	0.724			shoulder_angle_range	0.500
hip_mean	0.703			knee_range	0.390
knee_range	0.211	Right_Single_Support	2.158	all_max_dif	0.378
shoulder_angle_max	0.208			hipknee_dif	0.363
hip_min	0.193			knee_dif	0.321
all_max_dif	0.174	Left_Stance	2.093	Left_Single_Support	0.246
shoulder_angle_range	0.168			Right_Swing	0.235
ankle_min	0.158			Right_DoubleSupport	0.166
hip_max	0.138	Right_Swing	2.092	Left_Stance	0.137
hipknee_dif	0.127			knee_mean	0.132
knee_dif	0.066			ankle_range	0.101
hip_range	0.054	Left_DoubleSupport	1.891	Left_DoubleSupport	0.084
knee_mean	0.050			Right_Single_Support	0.083
shoulder_angle_min	0.036			Right_Stance	0.071
knee_min	0.032	Left_Swing	1.748	hip_range	0.010
ankle_range	0.000			Left_Swing	0.000

(ANN). As displayed in *Table 2*, all three models exhibited accuracy rates below 0.8 and yielded low F1-score values under 0.4. This suggests that while they demonstrated some level of performance in classifying patients into sarcopenia and non-sarcopenia groups, their ability to classify sarcopenia patients specifically was relatively low. Additionally, the MeanDecreaseGini coefficient derived from the RF classification model suggested a range of values between 1.7 and 2.6 for the eight variables, including 'support', 'swing' and 'stance', indicating little substantial difference among them.[29] Further details can be found in *Table 3* and *Figure 5*.

Finally, when using both pose estimation and smart insole outcome variables, the three models achieved accuracy rates of 1.00 (RF), 0.80 (SVM) and 0.96 (ANN). The corresponding F1-scores were 1.00 (RF), 0.73 (SVM) and 0.97 (ANN). As shown in *Table 2*, the three classification models achieved high levels of accuracy, with rates of 0.8 or higher, and demonstrated better classification than when using only one method, except for SVM. Moreover, the F1-score rates also suggested a high level of classification accuracy. These metrics demonstrate their remarkable ability to classify both sarcopenia and non-sarcopenia patients effectively, as well as to specifically identify sarcopenia cases with high accuracy. Furthermore, the RF classification model identified 'Hip_dif' (3.394), 'Hipankle_dif' (3.354) and 'Ankle_dif' (2.607) as the primary variables for distinguishing between the sarcopenia and control groups.[29] This is similar to the results achieved using only the pose estimation, as shown in *Table 3* and *Figure 6*.

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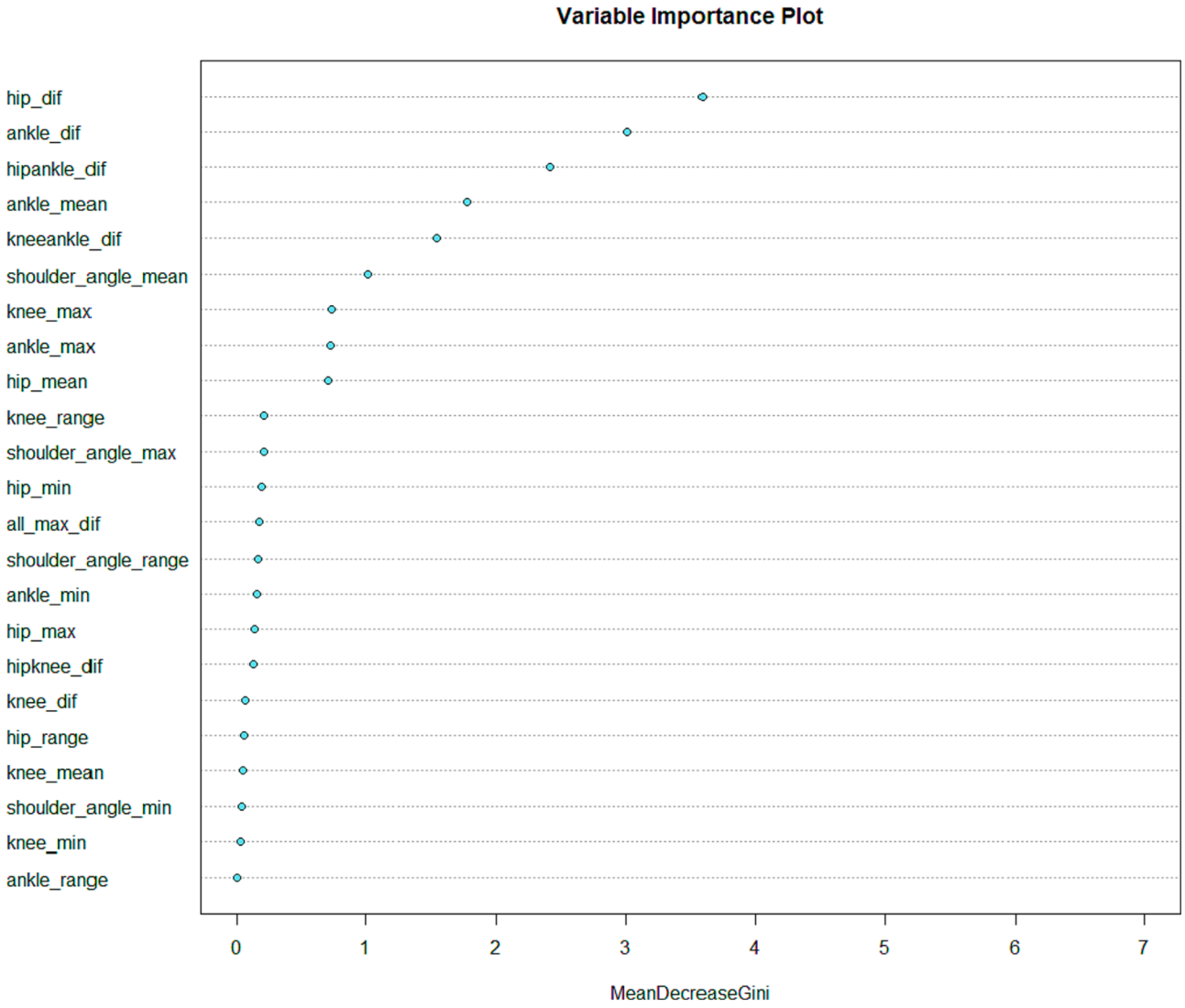

Figure 4 MeanDecreaseGini of open pose estimation obtained through random forest.

Discussion

The primary aim of this study encompasses two main objectives. First, we aimed to integrate recent advancements in the assessment of physical functions and apply them to the context of sarcopenia. Many studies have solely relied on sensors such as pressure plates or gyroscopes to measure physical performances.[30–32] Each of these methods possesses its own strengths and limitations. Therefore, our objective was to combine the advantageous aspects of these methods to establish more precise diagnostic criteria for evaluating bodily functions across various conditions, including sarcopenia. Our second objective was to differentiate individuals with sarcopenia from those with movement disorders by utilizing their physical functions. While numerous studies demonstrate the accuracy of tools like smart insoles and sensors in distinguishing between healthy individuals and patients, the significance of these findings can vary.[33–35] To address this, we introduced a classification model that incorporates the latest AI technique, pose estimation, along with a smart device, the insole.

Through the utilization of the aforementioned tools, we conducted an analysis using SVM, RF and ANN classification models. The results of this analysis revealed significant outcomes when comparing the physical functions between the sarcopenia group and the control group. When employing only the pose estimation technique, variables such as 'Hip_dif' and 'Ankle_dif', which denote the angle changes in joints after the initiation of movement from a static state, exhibited relatively high MeanDecreaseGini coefficients. These variables emerged as critical features for distinguishing between the sarcopenia and control groups. Furthermore, across the three classification models utilized (RF, SVM and ANN), accuracy and F1-score

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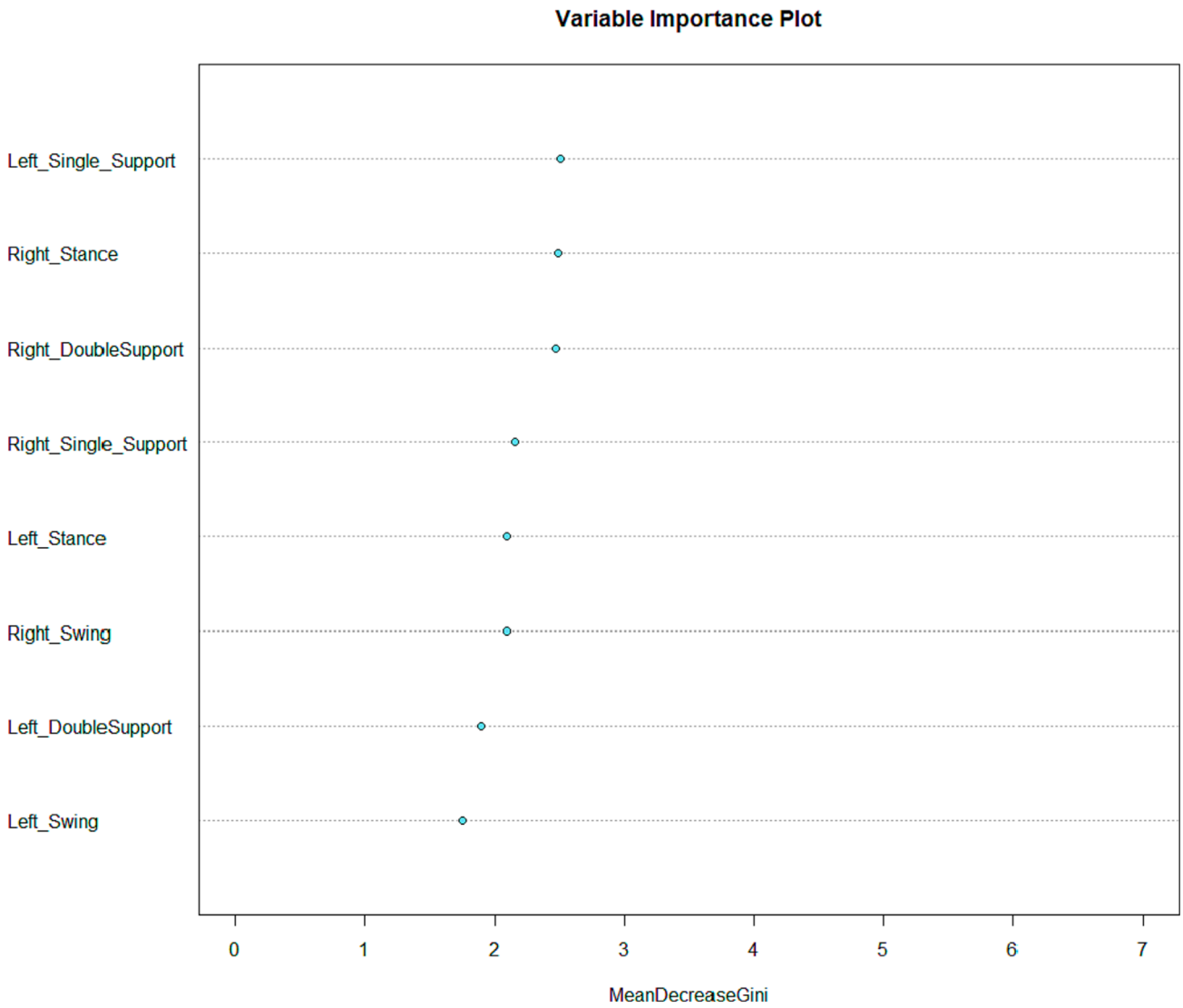

Figure 5 MeanDecreaseGini of smart insole obtained through random forest.

values exceeding 0.9 demonstrated the robustness and excellent classification performance of the models. While employing solely the smart insole, we observed comparable levels of significance across eight variables. However, when evaluating model performance metrics such as accuracy and the F1-score, using only the smart insole resulted in slightly diminished values in contrast to scenarios where solely pose estimation variables were employed or when pose estimation variables were combined with those from the smart insole. It is important to acknowledge that these outcomes could potentially be influenced by variations in patient weight and gait characteristics. When combining the variables from the smart insole and pose estimation, features for classifying sarcopenia were identified, particularly in variables like 'Hip_dif' and 'Hipankle_dif'. These variables showcased similar patterns to the results obtained when utilizing only pose estimation. Additionally, apart from the SVM model, the remaining two models exhibited F1-score and accuracy values exceeding 0.9, indicating a high level of classification accuracy and stability.

Currently, various guidelines for measuring physical performance in conditions, including sarcopenia, are being proposed by different institutions and countries.[2,3] However, diverse equipment options are being suggested for these measurements, and the subjective elements from assessors can differ significantly based on the equipment used. Therefore, in this study, we made efforts to minimize subjectivity by employing deep learning techniques and smart devices to measure physical performance. Notably, the use of pose estimation was particularly advantageous in overcoming the limitations of wearable devices attached to the body for measuring changes in the positions of body joints.[18,36] On the other hand, the smart insole excelled in capturing subtle

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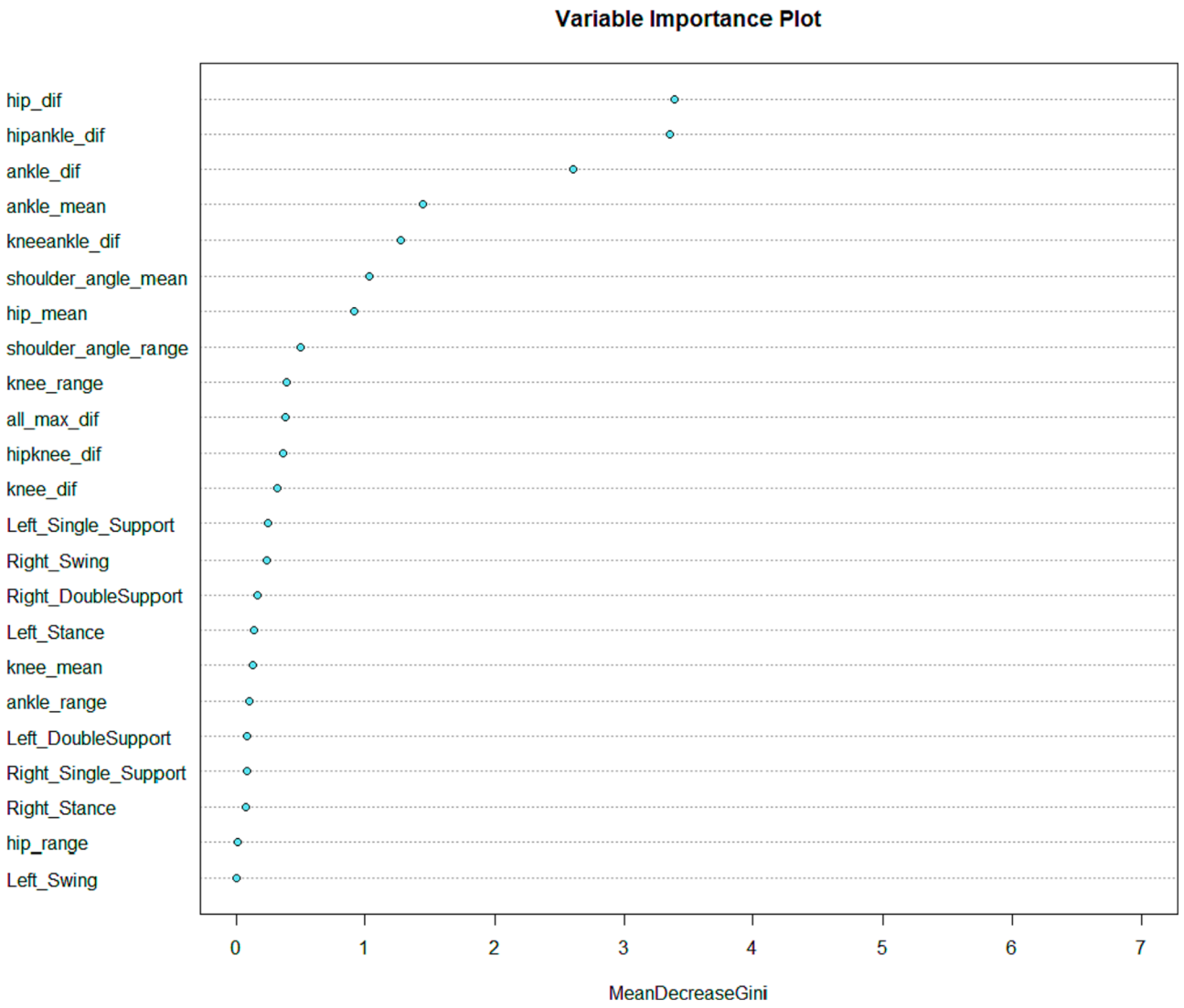

Figure 6 MeanDecreaseGini of open pose estimation and smart insole obtained through random forest.

pressure changes under the feet, enabling a more detailed differentiation of walking phases.[37,38]

In summary, the integration of AI-based detection tools and wearable technologies, including smart insoles and IMU-equipped earbuds, is profoundly reshaping patient care through real-time data acquisition. The amalgamation and effective utilization of such data have the potential to enhance the accuracy of diagnosis, prediction and treatment across a spectrum of conditions, including sarcopenia.

Limitations

Pose estimation is a technology that has various applications, including analysing body movement by tracking joint points in real time. However, there are several limitations to this technology that need to be addressed. First, the recognition rate may decrease in complex backgrounds or lighting conditions, affecting the accuracy of the results.[14,36] Additionally, recognition can become difficult when the camera's position or angle changes, adding another layer of complexity to the analysis.[14,39] Furthermore, the current pose estimation technology has a low recognition accuracy for hand and foot movements, especially during fast movements or complex actions. The human torso is also highly flexible, and there may be significant variations in angle and distance that this technology may not sufficiently reflect. It is worth noting that this technology operates based on image data and cannot utilize other information such as voice or touch. Finally, preconditions, such as the participants' clothing being sufficiently organized, and environmental restrictions may be necessary when applying this technology.

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Smart insoles have the potential to be an effective tool for monitoring health status by analysing walking patterns. However, they do have certain limitations that need to be addressed. These include the fact that they are restricted to analysing walking patterns and may not be suitable for other exercises or activities. Additionally, their accuracy may vary depending on the type of shoe and walking pattern, and they may be uncomfortable for some users to wear.[40] Smart insoles also rely on sensors, which can significantly increase power consumption, resulting in shorter battery life. Furthermore, privacy concerns may arise due to the collection of personal information, and vulnerable users such as the elderly or those with disabilities may not be able to use them effectively. Finally, smart insoles track health status based on previously collected data, and this often results in difficulty providing early warnings before the onset of a disease.

Finally, this study also presents certain potential limitations. Among patients diagnosed with sarcopenia, there existed a limited number of cases where independent walking was achievable without the utilization of assistive devices designed for walking facilitation. This restricted sample size introduced challenges during group comparisons, leading to discrepancies in characteristics such as gender and age. Additionally, during more detailed characteristic comparisons, limitations became apparent. To address this, supplementary tables were incorporated, detailing analysis outcomes for groups with matching characteristics (refer to *Tables S5*–*S7*). Comparison between these supplementary tables and the original analysis results in *Tables 2* and *3* did not reveal substantial differences. Furthermore, this study addressed 8 variables corresponding to walking stages using insoles and 23 variables corresponding to joint angles through pose estimation. However, the potential for considering additional variables exists; for instance, in the context of insoles, aspects like centre of pressure and foot pressure ratios could be explored. Similarly, concerning pose estimation, various other factors including speed and acceleration could be considered, indicating the inherent limitation in the number of variables explored within this study.

Conclusions

In our study, we explored the efficacy of a classification model that integrates pose estimation and smart insole technology. Our analysis encompassed data from 60 individuals without sarcopenia and 23 individuals diagnosed with the condition. Notably, the RF model, which incorporated features from both the smart insole and pose estimation data, yielded significant results, especially for the Hip and Ankle variables.

Recent advancements in measurement technology have greatly enhanced the precision of sarcopenia diagnosis, revealing new digital biomarkers across various assessment techniques. This evolution indicates a promising direction for the identification and utilization of more digital biomarkers in managing a range of disorders. The convergence of AI technologies with diagnostic and therapeutic approaches offers immense potential for improving interventions in conditions like sarcopenia.

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Conflict of interest statement

The authors declare no conflicts of interest.

Data availability statement

The data used in this study were collected at Gyeongsang National University Hospital, and inquiries about the data should be directed to the corresponding author.

Online supplementary material

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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