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RESEARCH ARTICLE

A Machine Learning Approach for the Classification of Falls and Activities of Daily Living in Agricultural Workers

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Research Ethics Committee of Seoul National University under IRB No. 2004/003-027.

ABSTRACT Population aging is a global trend, and the highest proportion of elderly people in the workforce per unit of population is found in agricultural areas. However, few systematic studies have been conducted on farmer falls in the field of agricultural machinery. This study focuses on the application of classification methods for monitoring devices to detect fall/nonfall movements of farmworkers, where agricultural biomechanical factors are considered in detecting activities of daily living. In this study, we recorded and analyzed original acquisition datasets of signals obtained from two accelerometers and one gyroscope for 40 healthy individuals who performed various falls and activities of daily living (ADLs). Spatial characteristics were used to train the machine-learning classifiers to distinguish between fall and non-fall events. Supervised machine learning experiments evaluated the effectiveness of the proposed approach: the k-nearest neighbors (kNN) and support vector machine (SVM) algorithms achieved roc auc-scores of 0.999 in distinguishing falls and ADLs (binary-class classification). Moreover, an artificial neural network (ANN) classifier showed the highest performance in terms of classification roc auc-scores of 1.0. The evaluation metric demonstrated the highest performance in the analysis and evaluation of the signal obtained from the S2 acceleration sensor with a measurement range of ±16 g. The proposed SVM classifier evaluations showed a 0.988 roc auc-score for sensor tests in multi-class classification, along with the highest performance in terms of the F1-score and Matthews Correlation Coefficient (MCC) over 84% in the multi-class classification model for distinguishing each of ADLs and Fall using ±16 g acceleration sensor.

INDEX TERMS Agricultural worker, fall-detection, human behavior recognition, machine learning, wearable sensor.

I. INTRODUCTION

United Nations (UN) has predicted that the world population will increase by 2.2 billion by 2050, from 7.5 billion to 9.7 billion [1]. This is approximately 1.3 times the current

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population. More food must be supplied as the number of people increases. However, the agricultural population that conducts agricultural production will continuously decrease and drop to 30% of the total population by [2], [3]. According to the World Bank (WB), the proportion of the world's rural population was 43.85% in 2020, representing a decrease of 22.53% since the start of the count in 1960. In contrast, the proportion of the aging population is rapidly increasing, particularly in these areas. Among the world's population, the proportion of the population aged 65 or older was 9.3% as of 2020, which is expected to steadily increase in the future to reach up to 16% [4]. In Korea, the number of elderly people is growing rapidly. Currently, the proportion of people aged over 65 years in the rural population is 42.5%, and is expected to exceed 60% within the next five years [5]. Social problems are emerging because of a lack of labor because of the decrease in population and rapid aging of society in rural areas.

According to a survey by the World Health Organization (WHO), older agricultural workers may be vulnerable to work-related injuries such as chronic musculoskeletal disorders or fractures, and the frequency of falls also increases from 28% to 42% as age increases from 65 to 70 years old [6]. The bone fracture in elderly caused by a fall showed the slowest healing rate. Furthermore, secondary complications such as pneumonia and bedsores can occur which can lead to death in the worst case. Elderly people who have experienced a fall may have difficulty in independent daily life due to the fear and psychological atrophy they feel in response to the fall accident, which can significantly reduce their quality of life [7].

As social problems of aging are emerging, interest in the activities of daily living (ADLs) of elderly people is increasing, and research in the healthcare field that targets elderly people is also rapidly increasing. ADLs encompass variety of daily movements performed by elderly people (e.g., dressing, eating, moving, and hygiene activities). In addition, the ADL index of elderly people is used as an analysis index to evaluate each subject's dependence on others during daily activities [8]–[10]. In early ADL studies, data were collected using questionnaires, which showed several limitations in collecting and analyzing numerous samples. To resolve these problems, a simple and automated system was used to collect ADL data of elderly people. The system is designed to be worn by the elderly in their daily life, and data is collected based on a simple ADL classification a sensor network. A Bayesian network model was used as the feature extraction method, and a hidden Markov model (HMM) was proposed as the classification method [12]. In this study, we have included falling as the one of the movements in ADLs. Several experiments have focused on distinguishing fall out of other various ADL movements.

Machine learning-based FDS (Fall Detection Systems) research refers that monitors observation targets in real-time and automatically warns people during an emergency [13]. In several European countries, research is underway to create a fall database based on a vast amount of metadata collected from elderly care facilities or living environment of the elderly [14]. A representative example is a study by the Farseeing Consortium [15], in which actual fall data were collected using an FDS based on inertial sensors in the living environments of elderly inpatients. The falls were photographed with the help of a caregiver or nurse using CCTV cameras installed in their environments. A total of 300 fall data points were collected from six institutions over three years, and the number of verified data points was 208. Currently, public access to only some of the data is restricted. Because these data correspond only to the motion that caused the fall, their application to algorithm research is limited; for example, they cannot be applied to machine learning-based fall detection models because of their unbalanced composition and non-separation from ADLs, and they cannot be utilized in many subsequent studies. However, other research teams have designed new ADL tests and fall simulation experiments to address these problems. Casilari *et al.* published the UMAFall dataset using data collected from the sensor of a smartphone and an inertial sensor attached to the body of the research participant. A study that classified falls by applying Bayes classification and four decision tree machine-learning models was performed [16]. Sucerquia *et al.* developed a fall detection system based on wearable sensors (an accelerometer and gyroscope) and released a new dataset. A threshold-based algorithm has been proposed [17], [18]. Giuffrida *et al.* attempted to detect falls using fall-mimicking experimental data published in the SisFall dataset. This study achieved higher accuracy compared to threshold-based fall classification studies [19].

Systematic approaches have received considerable attention in recent years. In addition, FDS research based on ambient sensors that can detect the residential environment to automatically detect falls in the elderly is increasingly being conducted. A multimodal sensor-based FDS is an interface system that considers the user environment, in which the computer receives, combines, and analyzes various information. This system can measure a user's specific environment, such as the user's voice and movement pattern, at the same time [20]. Droghini *et al.* proposed a technique for measuring people's motion data using floor speakers installed indoors and classifying them into daily movements and falls. In this regard, the fall detection system uses the development of floor acoustic sensors and machine-learning technology. It also presents an improved classification performance compared to previous studies [21].

The 4th industrial revolution technologies, such as the Internet of things (IoT), artificial intelligence (AI), and big data, are making a significant progress in research on rural environments. Recently, in the biosystems engineering field, the efficiency of farm operations and production has been promoted through the application of new technologies, such as machine learning and artificial neural network technology [22], [23]. Aiello *et al.* proposed a method of mapping the vibration risk using a machine learning algorithm with the signal measured from the IMU sensor for the purpose of farmer safety [24]. Patalas-Maliszewska *et al.* proposed an object recognition algorithm that automatically recognizes the work activities of manufacturing workers using a convolutional neural network model [25]. The research subjects of agricultural engineering technology are being expanded through the application of artificial intelligence systems, such as machine learning using data-based sensing technology and artificial neural networks, along with a new paradigm change. Moreover, the scope and scale of research are being greatly enlarged via the application of real-time monitoring technology, which is widely used in the health care field, to agricultural technology. Despite these paradigm shifts, few studies have been conducted on safe agricultural work activities of daily living that can directly affect agricultural workers.

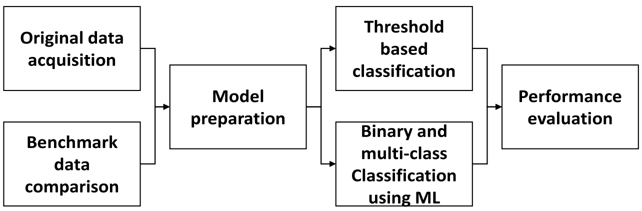

FIGURE 1. Schematic flow of the classification algorithm.

Accidental falls and ADLs that may occur during agricultural activities were mimicked and classified in agricultural simulation experiments using a supervised learning-based machine learning approach. Forty participants who were selected for distinguishing falls from nonfalls were assumed to be farmworkers, and seven types of falls and eight types of ADL movements, including possible motions, were performed repeatedly during agricultural work in a controlled environment. As the sensor, an inertial sensor that was capable of measuring two acceleration and one angular velocity signal was used. The sensor system was attached to each study participant's waist. The raw data were calculated using a benchmarked model and feature extraction method, and the model was trained by dividing the data into training and testing sets. The fall and ADL classification performance was assessed in terms of roc auc-score, accuracy, F1-score, and MCC using kNN, SVM, and ANN.

II. MATERIAL AND METHODS

Figure 1 is a schematic flow of the classification algorithm in this study. Our proposed dataset has been compared with a benchmark dataset (SisFall). Both datasets (Proposed and benchmark) were pre-processed with feature extract. The ML classifiers used kNN, SVM, and ANN. These are frequently used machine learning fall detection systems. And then we evaluated performance criteria using roc auc-score, accuracy, f1-score, and MCC.

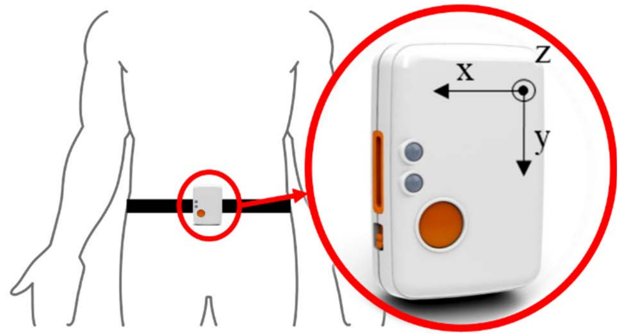

FIGURE 2. A device that was used for signal acquisition. The coordinates and force directions of the device when attached to the participant's waist are specified.

A. ORIGINAL DATA ACQUISITION

Fall and agricultural work ADL-mimicking experiments (fall &Ag_ADL_M_E) were performed on 40 subjects who provided signed consent. The age range of the subjects was 22-51 years, with 25 male subjects (age: 29.4 $\pm$ 6.5, height: 175.6 $\pm$ 5.6 cm, and weight: 77.2 $\pm$ 12.6 kg) and 15 female subjects (age: 25.5 $\pm$ 4.7, height: 161.4 $\pm$ 4.4 cm, and weight: 53.2 $\pm$ 3.6 kg). None of the subjects had problems with the musculoskeletal system or underlying diseases. The fall- and agricultural ADL-mimicking experiment was approved by the Research Ethics Committee (IRB No. 2004/003-027) of Seoul National University and all participants were provided with safety guidelines and detailed information about the experiment and the established experimental protocol before the experiment.

Three-axis inertial sensors (SHIMMER3, ShimmerTM, Ireland) were used to capture the acceleration and angular velocity for falls and Ag_ADL_M_E. The inertial sensors used in the experiment consisted of two channels of acceleration detectors on three axes and one channel of angular velocity detectors on three axes, each with ranges of $\pm$ 2 g, $\pm$ 16 g, and $\pm$ 2000 °/s. The sensitivity of the acceleration detector with an output range of $\pm$ 2 g was 600 mV/g, and the sensitivity of the acceleration detector with an output range of $\pm$ 16 g was 0.732 mg/LSB. The sensitivity of the angular velocity detector was 131 LSB/dps and the communication interface was operated using I2C. The inertial sensors used in the experiments were attached to the subjects' waists, and the directions of the three-axis acceleration and angular velocity obtained from the inertial sensors are presented in Figure 2 [17]. The measured signals were transmitted and stored via real-time Bluetooth.

During the fall mimicking experiment, the subjects wore pad-type hip joint protectors, protective helmets, cervical spine protectors, and wrist and knee joint protectors, as shown in Figure. 3(a). Figure 3(b) shows the situation of Fall01, which is slip and fall. As shown in Figure 3(c), and Figure 3(d) is the hip-impact status after falling. The fall mimicking experiments were performed after installing a foam mattress to prevent hip joint injury.

Seven falls and eight ADLs were proposed, as presented in Tables 1 and 2. The time and trials were designed for each fall and ADL during agricultural work. As presented in Table 1, the most frequently occurring fall from agricultural work was selected as Fall01–Fall03 [26]; Fall04 corresponds to a fall while riding up a tractor [27]; Fall05 is a fall that is caused by a long-term squatting posture, especially during agricultural work such as weed removal; Fall06 is a fall that is caused by long-term work with stooping tasks, which likely mimics pepper harvesting work; and Fall07 is a fall that is caused by loss of balance while carrying objects [28]–[30]. All falling motions were repeated five times.

FIGURE 3. Overview of the proposed methodology for the fall experiment: (a) A schematic view of a participant wearing a sensor and joint protection guards; (b) Fall01 slip and fall; (c) the impact phase when the hips touch the floor; and (d) the resting phase after the fall.

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Table 2 shows walking, sitting, standing, ascending, and descending, with ADLs designed to simulate routine farming operations. In addition, agricultural processes such as harvesting, packing, and transportation, including squatting (e.g., weed removal), stooping (e.g., pepper harvesting), and lifting (e.g., box lifting), are known to be heavy workloads to the skeletal system. ADL01 to ADL03 were identified as ADLs investigated in previous studies, namely, walking up and down ladders instead of climbing stairs and sitting down. They reflect additional movements such as standing up. ADL04 is a simulation of a furrow jump that crosses between furrows lightly, and ADL05 uses a tractor's tread plate to simulate the movement of climbing on the tractor [31]–[33]. In addition, ADL06 was designed to simulate long-term squatting tasks, such as harvesting in agriculture, and ADL07 was chosen to simulate tasks in a bent position, such as harvesting peppers. Finally, we defined ADL08 as a box-loading task that is often conducted for transportation during agricultural operations [34]. All ADL movements designed in this study consisted of movements that commonly occur in agricultural work (Table 2). The selected motion was repeated five times.

TABLE 1. Types of falls considered in this study.

Code	Activity	Trials	Time
Fall01	slip and fall	5	15s
Fall02	trip and fall	5	15s
Fall03	bump with something after fall	5	15s
Fall04	fall while getting into the tractor (agricultural machine)	5	15s
Fall05	squat task in simulated weed removal work	5	15s
Fall06	stoop task in simulated pepper harvesting work	5	15s
Fall07	balance loss with a load-carrying	5	15s

TABLE 2. Types of ADLs based on motions that were used to mimic agricultural work.

Code	Activity	Trials	Time
ADL01	walking (60 beats per minute, 1 cycle foot step)	5	25s
ADL02	going up & down a ladder (3 step going up)	5	25s
ADL03	sitting & standing (squatting)	5	15s
ADL04	jumping without falling (between furrows)	5	15s
ADL05	getting into a tractor※, remaining there and getting out of the vehicle	5	15s
ADL06	squatting task in simulated weed removal work	5	25s
ADL07	stooping task in simulated pepper harvesting work	5	25s
ADL08	hard carrying using a box loading	5	25s

B. BENCHMARK DATA COMPARISON

A fall and ADL classification model was also learned using the SisFall dataset, which is an open dataset, in addition to the dataset obtained through the ADL mimicking experiment for fall detection. To obtain the SisFall dataset, 34 types of fall and ADL mimicking experiments were performed on a total of 38 subjects, who were classified into two groups, namely, 23 subjects aged 19-30 years and 15 subjects aged 60-75 years old; this dataset contains a total of 4505 data samples. The dataset consists of 1798 fall data points of 15 types and 2707 ADL data points of 19 types. For safety reasons, all subjects aged 60 to 75 years participated only in the ADL experiment, except for one subject who was trained in martial arts in the elderly group. In this benchmark dataset, two acceleration channels with ±8 g and ±16 g ranges and one angular velocity channel with a range of ±2,000 °/s were detected using the fall detection system (FDS) developed by the research team. The acceleration and angular velocity were measured to acquire three-axis data, and data storage and wireless data transmission functions were performed using internal memory. The FDS sensor was attached to the subject's waist, and a fall-and ADL-mimicking experiment was performed. Table 3 presents the main contents and differences between the SisFall and Falls&Ag_ADL_M_E datasets. The SisFall dataset consists of 4505 data samples, of which 1798 are fall data, which are classified into 15 types, and 2707 are ADL datasets, which are classified into 19 types [17]. Because Falls&Ag_ADL_M_E was a young subject dataset for safety reasons, we used the model with only 3537 data samples of young subjects out of the 4505 samples in the SisFall datasets for comparison with a similar age group.

TABLE 3. SisFall vs. Fall&Ag_ADL_M_Es dataset comparison.

	SisFall	Falls&Ag_ADL_M_E
Subjects	38 participants - 23 young adult - 15 elderly	40 young adult - 25 male - 15 female
Sensors	Self-developed FDS* 2 x 3 axial accelerometer 1 x 3 axial gyroscope	Shimmer 3 TM 2 x 3 axial accelerometer 1 x 3 axial gyroscope
Sampling rate	200 Hz	200 Hz
Axis orientation	- x-axis: right side of the participant - y-axis: gravity direction - z-axis: forward direction	- x-axis: right side of the participant - y-axis: gravity direction - z-axis: forward direction
Sensor attachment	Subject waist	Subject waist
Activities	-15 falls -19 ADLs	- 7 falls - 8 ADLs
Samples of ADL/Falls	2707/1798	1597/1339
Algorithm	Threshold-based algorithm	Supervised learning algorithm
Accuracy	n/a	See the result below
Subjects	38 participants - 23 young adult - 15 elderly	40 young adult - 25 male - 15 female
Sensors	Self-developed FDS* 2 x 3 axial accelerometer 1 x 3 axial gyroscope	Shimmer 3 TM 2 x 3 axial accelerometer 1 x 3 axial gyroscope

* FDS: Fall detection system

C. MODEL PREPARATION

The acceleration and angular velocity data measured through Falls&Ag_ADL_M_Es may have been affected by noise and disturbance during measurement, and these noise components may have affected the performance of the fall classification model to be developed. Thus, the raw data that were initially measured required pre-processing, and a low-pass filter (LPF) was used to block the high-frequency components of the most common noise [18], [35].

The fall/non-fall classification model obtained through the mimicking experiment was composed of two types of data frames (SisFall dataset and Fall&Ag_ADL_M_Es) using sensor signals as independent variables. Each dataframe consisted of components of three observation values from the Shimmer 3 sensor: Sensor 1 (acceleration, ±2 g), Sensor 2 (acceleration, ±16 g), and Sensor 3 (angular velocity, ±2000/ °s). A data frame was constructed through a feature extraction process using the proposed method [36]–[38]. S_{norm} is defined as the Euclidean norm of acceleration in the 3-axis plane and can be calculated by $S_{norm} = \sqrt{(s_x^2 + s_y^2 + s_z^2)}$, which is used to describe the spatial variation of acceleration during movements in the 3D plane of the body. S_{hori} is defined as the Euclidean norm of acceleration in the horizontal plane (x, z-plane) and can be calculated by $S_{\mathrm{hori}} = \sqrt{(s_x^2 + s_z^2)} S_{\mathrm{hori}} = \sqrt{(s_x^2 + s_z^2)}$,, which is used to describe the spatial variation of acceleration during movements in the horizontal plane of the body. S_{verti} is defined as the Euclidean norm of acceleration in the vertical plane (y, z-axis) and can be calculated by $S_{verti} = \sqrt{(s_y^2 + s_z^2)}$, which is used to describe the spatial variation of acceleration during movements in the vertical plane of the body. Nine variables were extracted, and additional features for statistical variables such as the mean, standard deviation, variance, maximum, minimum, range, kurtosis, skewness, and correlation coefficient were extracted based on these nine variables. Therefore, the feature vector extracted from the sensor of one channel had 54 independent variables. m represents the total number of samples in the data frame, as listed in Table 4 [39].

TABLE 4. Description of feature vector for machine-learning algorithm.

Feature Vector, F = (f1, f2, …, f54) ∈ R54	Feature Description	
$f_1 \sim f_3$	Mean for x, y, and z axis:	$\mu = \frac{1}{m}\sum_{i=1}^{m} x_i$
$f_4 \sim f_6$	Mean for *norm*, *verti* and *hori*:	
$f_7 \sim f_9$	Standard deviation for x, y, and z axis:	$\sigma = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(x_i-\mu)^2}$
$f_{10} \sim f_{12}$	Standard deviation for *norm*, *verti* and *hori*:	
$f_{13} \sim f_{15}$	Variance for x, y, and z axis:	$\sigma^2 = \frac{1}{m}\sum_{i=1}^{m}(x_i-\mu)^2$
$f_{16} \sim f_{18}$	Variance for *norm*, *verti* and *hori*:	
$f_{19} \sim f_{21}$	Maximum for x, y, and z axis:	$\max(a_i)$
$f_{22} \sim f_{24}$	Maximum for *norm*, *verti* and *hori*:	
$f_{25} \sim f_{27}$	Minimum for x, y, and z axis:	$\min(a_i)$
$f_{28} \sim f_{30}$	Minimum for *norm*, *verti* and *hori*:	
$f_{31} \sim f_{33}$	Range for x, y, and z axis:	$\mathrm{range}(a_i) = \max(a_i) - \min(a_i)$
$f_{34} \sim f_{36}$	Range for *norm*, *verti* and *hori*:	
$f_{37} \sim f_{39}$	Kurtosis for x, y, and z axis:	$\mathrm{kurtosis} = \frac{\sum_{i=1}^{m}(x_i-\mu)^4}{m\sigma^4}$
$f_{40} \sim f_{42}$	Kurtosis for *norm*, *verti* and *hori*:	
$f_{43} \sim f_{45}$	Skewness for x, y, and z axis:	$\mathrm{skewness} = \frac{\sum_{i=1}^{m}(x_i-\mu)^3}{m\sigma^3}$
$f_{46} \sim f_{48}$	Skewness for *norm*, *verti* and *hori*:	
f_{49}	Correlation coefficient(CC) between x and y	$\mathrm{Corr}_{ab} = \frac{1}{m}\sum_{i=1}^{m}\left(\frac{a_i-\mu_a}{\sigma_a}\right)\left(\frac{b_i-\mu_b}{\sigma_b}\right)$
f_{50}	CC between x and z	
f_{51}	CC between y and z	
f_{52}	CC between *norm* and *verti*	
f_{53}	CC between *norm* and *hori*	
f_{54}	CC between *verti* and *hori*	

m: Determined size of dataset (or phase); *norm*: Euclidean norm of triaxial sensor signal; *verti*: Euclidean norm of sensor signal in the vertical (sagittal) plane; *hori*: Euclidean norm of sensor signal in the horizontal plane.

III. CLASSIFICATION MODEL

A. K-NEAREST NEIGHBORS (kNN)

The kNN algorithm is a method for classifying data x by majority voting. It determines which class of k data is distributed close to the coordinate around that located when data x is newly entered. When the data are entered, the minimum distance between the new data and the existing training data is calculated. From the k data points around the entered data, we classify the data by determining to which class the training data are assigned. Equation (1) corresponds to the Euclidean distance calculation. Therefore, once the learning and test data are prepared, the distances between the data are calculated to determine the type of nearest neighbors from the data. The kNN model utilized the Python-based scikit-learn library to implement the kNN, and the k value was set to five. Seventy percent of the datasets were defined as training data and the remaining 30% were used as test data and classified.

$$d\left(X_i, X_j\right) = \sqrt{\left(x_{i1} - x_{j1}\right)^2 + \cdots + \left(x_{in} - x_{jn}\right)^2} \quad (1)$$

$$R_k^X = \left\{X \in R^n, d\left(X, X_i\right) \leq d\left(X, X_k\right)\right\} \quad (2)$$

where d (Xi, Xj) denotes the distance between samples Xi and Xj and R_k^X denotes the group that belongs to the nearest neighbor among the k-nearest neighbors of the new feature vector X. Then, the newly entered feature vectors are assigned to the class and belong to the nearest neighbor k [40].

B. SUPPORT VECTOR MACHINES (SVM)

Support vector machines (SVMs) are multipurpose machine learning models that are frequently used in linear and nonlinear classification, regression, and anomaly detection and have been used mainly for binary classification models after feature extraction [41]. The initial linear support vector machine (SVM) theory was proposed by Vapnik *et al.* In 1963, it was used to solve image recognition problems such as the recognition of handwritten numbers and faces. Recently, Liu *et al.* applied SVM algorithms to models that classify falls and non-falls, which indicated highly satisfactory performance [42].

The SVM classifier used in this work utilized a linear support vector machine (SVM) provided by the Python-based scikit-learn library, which defined 70% of the datasets as training data and the remaining 30% as test data to train the model. Equations (3) and (4) refer to the process of finding the boundary between hyperplanes that can separate samples of classes belonging to different groups. Given the training data $X = \{X_1, X_2, X_3 \ldots\ldots, X_{N-1}, X_N\}$ labels that correspond to hyperplanes can be found at $Y = \{y_1, y_2, y_3 \ldots\ldots, y_{N-1}, y_N, y_i \in [1, -1]\}$ where w and b are the parameters that represent the hyperplane.

$$w^T \cdot X_i + b \geq +1, \quad y_i = +1 \quad (3)$$

$$w^T \cdot X_i + b \geq -1, \quad y_i = -1 \quad (4)$$

The margin of a hyperplane is the distance between the hyperplanes that pass through each support vector. Geometrically, the distance between the two hyperplanes is $\frac{2}{\|w\|}$ when the margin is obtained, and the SVM is defined as an algorithm that maximizes the margin.

C. ARTIFICIAL NEURAL NETWORK (ANN)

Artificial neural networks (ANNs) are machine-learning algorithms inspired by biological neural networks (where the brain is considered particularly important in the central nervous system of animals) and are used in statistics and cognitive science. ANNs are represented by the interconnection of neural systems from various input variables to the output, and artificial neural networks (ANNs) can be represented as mathematical functions that are configured to represent complex relationships between inputs (independent variables) and outputs (dependent variables).

$$a^{l+1} = \sigma\left(W^l a^l + b^l\right), \quad (5)$$

Here, a^l is the neuron value of layer l (a_i^l represents the value of neuron i of layer l), W represents the weight matrix between layers l and l + 1, b^l represents the bias associated with neurons in layer l, and σ represents the activation function. The ANN implemented in this work is a two-layer feedforward network that consists of sigmoid hidden and output neurons, where softmax is used as the final output short activation function (Figure 4). The error function uses sparse categorical cross-entropy and a stochastic gradient descent (SGD) optimizer. We defined a simple artificial neural network (ANN) model using Keras with a TensorFlow backend. The performance of the model was evaluated using data frames that were divided into training (70%) and testing (30%) sets. The test results were verified through holdout cross-validation using the average of the results of five repeats.

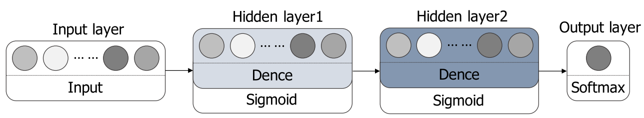

FIGURE 4. Implementing a simple ANN model with TensorFlow/Keras.

The detailed parameter setting of the classifiers is shown in Table 5. Initially, default values were used when selecting model parameters. Finally, we determined the value of the parameters through the observation responses by slightly changing those settings.

TABLE 5. Parameter setting for Machine learning model of the benchmark.

model	parameters
kNN	neighbors : 5, leaf_size : 30, metric : 'minkowski'
SVM	Linear Support Vector Classification, tol : 1e-8, C : default, dual : false
ANN	Basic neural network, 3 layers, optimizer : 'SGD', loss : 'sparse_categorical_crossentropy', epochs:500, batchsize:250

D. PERFORMANCE EVALUATION CRITERIA

We evaluated the model using the machine learning method for the performance evaluation of the three (kNN, SVM, and ANN) classification models proposed in this work. In this

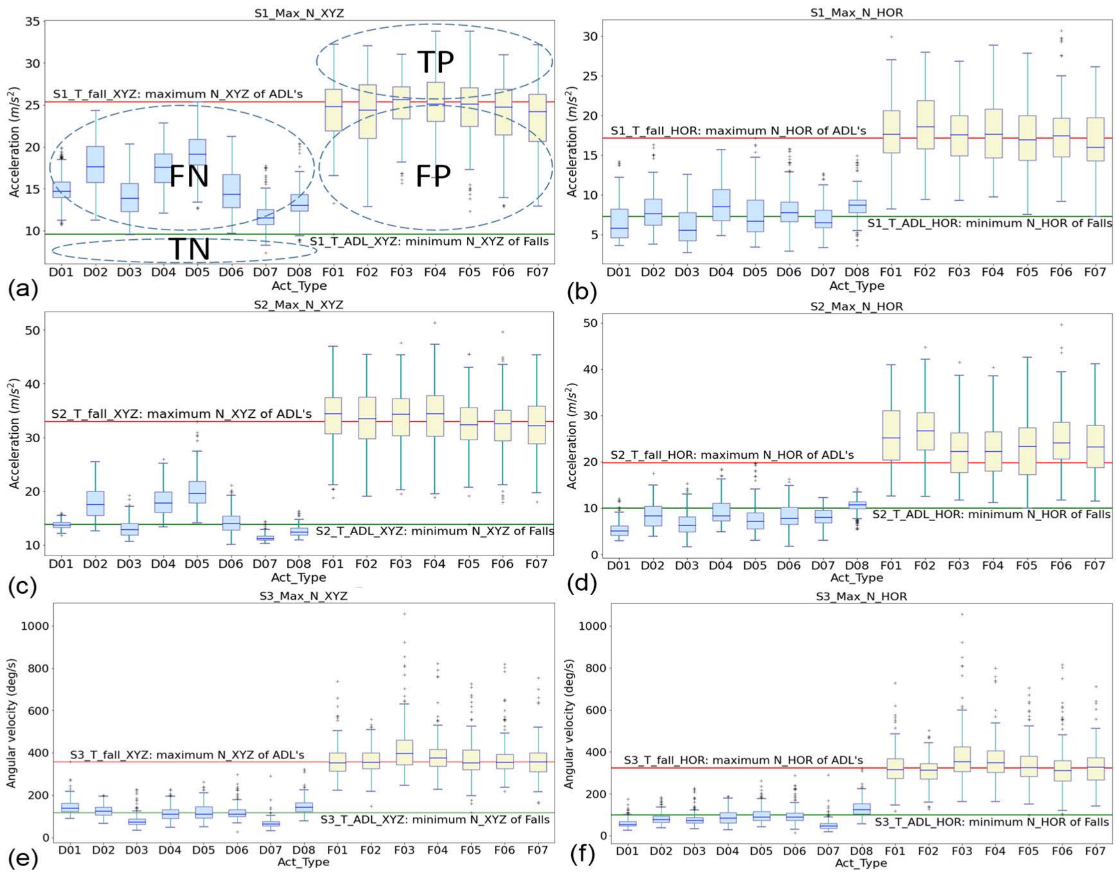

FIGURE 5. **Illustration of the S_{norm} and S_{hori} distributions of falls and ADLs in agricultural work. The left 8 activities represent ADLs, and the right 7 activities represent falls. (a) and (b): Boxplots of the maximum S_{norm} and S_{hori} values for falls and ADLs using sensor 1 (acceleration ±2 g). (c) and (d): Boxplots of the maximum S_{norm} and S_{hori} values for falls and ADLs using sensor 2 (acceleration ±16 g). (e) and (f): Boxplots of the maximum S_{norm} and S_{hori} values for falls and ADLs using sensor 3 (angular velocity: ±2000 deg/s).**

work, the positive condition was defined as the subject's fall, and the negative condition was the subject's performance of routine ADL behavior without falling [37]. The fall detection results are classified into four cases: true positive (TP), false positive (FP), true negative (TN), and false negative (FN). In fall detection systems, the results from FP and FN are evaluated as good performance classifiers [43]. Sensitivity, specificity, positive prediction value (PPV), negative prediction value (NPV), and accuracy were used as classification performance evaluation metrics, which correspond to the typical performance evaluation criteria for binary classification tests [44]. Sensitivity (or recall) is the ability to detect falls, and PPV (or precision) represents the quality of accurate fall detection. The sensitivity, specificity, precision, and accuracy show effective evaluation results for human activity classification on unbalanced datasets [45], [46].

ROC (Receiver Operating Characteristics) AUC (Area Under Curve) is the area under the roc auc curve that takes into account all possible classification thresholds. If the roc auc-score is closer to a value of 1, the prediction model is reliable, which can be one of the metrics used to evaluate the performance of the model. Accuracy is the proportion of the true test results among the total results, and the formula is presented in Equation (6). The sensitivity and precision were calculated using Equations (7) and (8), respectively. Higher sensitivity, specificity, precision, and accuracy values indicated better system performance of the applied model. The F1-score is the harmonic mean of the precision and sensitivity, which is used as a criterion for fairness in class performance for an unbalanced class distribution [36]. The formula for the F1-score is presented in Equation (9). In addition, the Matthews correlation coefficient (MCC) is used as a basis for assessing the quality of binary classification or multiclass classification of machine learning, where perfect prediction corresponds to a classification value of +1 and random prediction to a value of −1. Random prediction produces meaningless values. The result is usually determined to be reliable if the MCC value is 0.4 or higher. The MCC formula is presented in (10) [47].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

$$Sensitivity(orrecall)$$

$$= \frac{TP}{TP + FN} \tag{7}$$

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

$$F1\_score = 2 \times \frac{sensitivity \times precision}{sensitivity + precision} \tag{9}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FN)(TP + FP)(TN + FN)(TN + FP)}} \tag{10}$$

E. STATISTICAL ANALYSIS

For static evaluation, the difference between the benchmark data and the proposed data group is compared with Student's t-test. The 3 or more groups of comparison used ANOVA, and a post-hoc-test was performed through Tukey's HSD.

IV. RESULTS

A. THRESHOLD-BASED FALL DETECTION

Threshold-based classification assessed the performance of using the feature vectors S_{norm} and S_{hori}, which are the maximum and minimum threshold values, respectively, to classify falls and ADLs in agricultural work. All the data acquired in this study were analyzed after removing high-frequency noise components through preprocessing. Previous studies [37] found that threshold-based fall detection could be achieved using simple feature vectors, such as S_{norm} and S_{hori}. This threshold-based classification has the advantages of low computational cost and simplicity compared to machine learning or regression analysis, and is widely used for high-speed fall/non-fall classification. The threshold is determined using the maximum distributions of S_{norm} and S_{hori}. The distributions of falls and ADLs in agricultural work are shown in Figure 5. Figure 5(a), (b), and Figure 5(c) and (d) show the signal analyses from the accelerometers with measurement ranges of ±2 g and ±16 g. Figure 5(e) and (f) show the signal distribution measured by the angular velocity sensor. Table 6 presents the red horizontal line that indicates the maximum S_{norm} and S_{hori} boundaries of agricultural ADL measurements in each plot, and the green horizontal line that represents the minimum S_{norm} and S_{hori} boundaries of the fall measurement data.

TABLE 6. Measurement of the threshold-based classifier (using SNU_ag_fall_5Hz LPF).

		S1 (m/s^2)	S2 (m/s^2)	S3 (°/s)
Fall threshold	maximum S_{norm} of ADL	25.348	32.904	358.472
	maximum S_{hori} of ADL	17.138	19.737	323.680
ADL threshold	minimum S_{norm} of falls	9.554	13.845	117.938
	minimum S_{hori} of falls	7.266	9.980	98.361

Two thresholds were established for fall and ADL classification during agricultural work using the maximum and minimum values of S_{norm} and S_{hori} that are specified in Figure 5 and Table 6. As shown in Figure 5(a), the data that are distributed above the red horizontal line are true positive (TP) data; namely, this line is the threshold that determines a fall, and the data that are distributed below the green horizontal line are true negative (TN) data; namely, this line is the threshold that determines an ADL. In addition, false positives (FPs) and false negatives (FNs) were distributed between the red and green horizontal lines. Falls and non-falls were classified according to the determined values corresponding to each label.

Table 7 presents performance metrics of the threshold-based classifier that were analyzed based on the falls and ADLs in agricultural work, as shown in Figure 5. The results show that the S2 accelerometer (measurement range: ±16 g) and the two-axis (x, z horizontal plane) component achieved classification performance with 72.7% accuracy, 73.05% sensitivity, 69.86% precision, and 71.42% f1-score.

TABLE 7. Results of the threshold-based classifier using proposed dataset. (SNU_ag_Fall&ADL.)

%	S1 (±2g)		S2 (±16g)		S3 (±2000dps)	
	S_{norm}	S_{hori}	S_{norm}	S_{hori}	S_{norm}	S_{hori}
accuracy	22.26	49.73	48.83	<u>72.70</u>	53.70	62.32
recall	45.68	52.89	52.97	<u>73.05</u>	52.97	52.97
precision	28.94	46.63	45.85	<u>69.86</u>	50.41	61.14
f1-score	35.43	49.56	49.15	<u>71.42</u>	51.66	56.76
MCC	-59.96	-0.14	-1.83	<u>45.35</u>	7.30	23.86

Note: Underlined results represent the best performance of threshold.

B. MACHINE LEARNING-BASED FALL DETECTION

In this study, a machine-learning-based fall classification model was also implemented, and three methods (kNN, SVM, and ANN) were applied for classification. The experimental solution mimicked previous research methods [37], [39]. The dataset included simulated falls and ADL behaviors that imitated agricultural work, while other SisFall datasets included ADLs and simulated falls. In addition, the performance of the implemented machine-learning-based fall classification model was compared and evaluated for two categories (binary-class classification and multiclass classification).

1) BINARY-CLASS CLASSIFICATION (FALL/NONFALL)

Figure 6 shows the roc auc score compared with both datasets using the kNN, SVM and ANN classifiers, the evaluation metrics of roc auc-score using the 16 g acceleration data were 0.0438, 0.0095 and 0.0950 higher than those for the benchmark dataset. There were statistically significant differences between group means as determined by t-test ($p < 0.05$). Both datasets (benchmark and Proposed) demonstrate a reliable prediction in the SVM model.

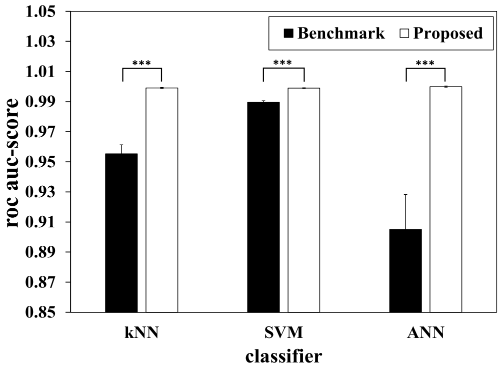

FIGURE 6. Comparison of binary-class classification of roc auc-score for benchmark and proposed dataset on kNN, SVM and ANN classifier using 16g acceleration sensor. (Student's t-test, ***p < 0.001.)

Table 8 presents evaluation results (roc auc-score, accuracy, F1-score, and MCC) of the binary-class classification models for falls and ADL behavior. Tables 8(A) and (B) present the test results of kNN-, SVM-, and ANN-based fall classification models that were implemented using benchmark and proposed datasets. In the benchmark dataset, classification was realized with 0.992 roc auc -score, 99.25% accuracy, 99.22% F1-score, and 98.49% MCC using the SVM classifier. On the proposed dataset, the best binary classification evaluation performance, with 1.0 roc auc-score, 99.84 accuracy, 99.83 F1-score, and 99.69 MCC, was realized by the ANN model. The best performance on proposed datasets was achieved when acceleration sensors that could measure the ±16 range were used. In particular, fall classification models that were trained using the experimental data measured with an accelerometer (Acc_16 g) with a measuring range of ±16 g achieved accuracy, F1-score, and MCC that exceeded 99%. The roc auc-score, accuracy, F1-score, and MCC of the ANN classification model using the proposed dataset were 0.095, 17.41%, 17.22%, and 34.34% higher, respectively than those using the benchmark dataset. There were statistically significant differences between benchmark and proposed data set groups as determined by Student's t-test. In addition, for the fall classification models that were trained using the proposed dataset, the metrics of roc auc-score, accuracy, F1-score, and MCC for the acceleration data were higher than those for the angular velocity data. This result supports the finding of previous studies that it may be practical to apply only acceleration information when implementing a machine-learning-based fall detection system [36], [48]. However, there are no significant differences between two acceleration sensors (8g vs 16g and 2g vs 16g) using the SVM classifier.

2) MULTI-CLASS CLASSIFICATION

Table 9 presents the evaluation results (roc auc-score, overall-accuracy, F1-score, and MCC) of the multi-class classification models for falls and ADL behavior. Tables 9(A) and (B) show the performance of the models on the benchmark and the proposed dataset. The experimental

TABLE 8. Binary-class classification results of the machine learning model and The roc auc-score, accuracy, F1-scores, and MCC ± SE.

model	metric	Acc_8g	Acc_16g	Gyro
kNN	roc auc-score	0.962±0.0171	0.955±0.0059	0.875±0.0085
	accuracy(%)	95.57±0.511	95.53±0.575	87.42±0.844
	F1-score(%)	95.44±0.532	95.40±0.602	87.40±0.902
	MCC(%)	91.14±1.022	91.06±1.153	74.99±1.715
SVM	roc auc-score	0.992±0.0025	0.989±0.0011	0.966±0.0047
	Accuracy(%)	99.25±0.240	98.95±0.108	96.63±0.449
	F1-score(%)	99.22±0.252	98.92±0.106	96.50±0.278
	MCC(%)	98.49±0.478	97.93±0.230	93.27±0.464
ANN	roc auc-score	0.698±0.0172	0.905±0.0233	0.725±0.0190
	Accuracy(%)	65.53±2.480	82.43±2.569	68.15±2.235
	F1-score(%)	64.72±4.001	82.61±2.648	69.50±1.647
	MCC(%)	32.53±3.735	65.35±5.077	36.92±4.142

(A) BENCHMARK DATASET (SISFALL)

model	metric	Acc_2g	Acc_16g	Gyro
kNN	roc auc-score	0.998±0.0014	0.999±0.0009	0.985±0.0010
	accuracy(%)	99.78±0.136	99.91±0.093	98.44±0.111
	F1-score(%)	99.76±0.146	99.90±0.100	98.32±0.153
	MCC(%)	99.55±0.273	99.82±0.187	96.87±0.234
SVM	roc auc-score	0.996±0.0037	0.999±0.0008	0.991±0.0012
	accuracy(%)	99.58±0.372	99.89±0.079	99.13±0.122
	F1-score(%)	99.53±0.437	99.88±0.085	99.05±0.146
	MCC(%)	99.14±0.761	99.78±0.158	98.25±0.245
ANN	roc auc-score	0.998±0.0013	1.0±0.00003	0.993±0.0021
	accuracy(%)	99.67±0.079	99.84±0.100	95.52±1.495
	F1-score(%)	99.64±0.084	99.83±0.107	95.25±1.632
	MCC(%)	99.33±0.158	99.69±0.200	91.10±2.992

(B) PROPOSED DATASET (SNU_AG_FALL&ADL)

Note: Underlined results represent the best performance of machine learning model.

results calculate the macro average and one versus rest (OVR) easily used in multi-class classification to compute metrics independently for each class and to take an average to treat all classes equally (Tran *et al.*, 2018). According to Table 9, the SVM classifier outperformed the other models in multiclass classification using data measured from the accelerometer (Acc_16 g) with a measurement range of ±16 g. The roc auc-score of the SVM model using the data that were measured from Acc_16 g were 0.991 and 0.989 for the multi-class classification model with the benchmark dataset and the proposed dataset. The roc auc-score was 0.003 higher than the proposed dataset. However, another evaluation metric of overall accuracy, f1-score, and MCC using the proposed dataset were 1.51, 9.55, and 2.38% higher, respectively, than those using the benchmark dataset. There were statistically significant differences between groups determined by Student's t-test(p-value < 0.5).

Table 9 presents the performance results of a multi-class classification model. The SVM classifier using the Acc_16 g sensor model showed the best evaluation performance. The statistical reliability was evaluated by comparing the metric of prediction rate.

Figure 7 shows the confusion matrix of the fall and ADL multi-class classification models using Acc_16 g sensor datasets. Each row of the matrix represents an actual class while each column represents a predicted class. The model consists of nine-class, eight of which are ADL classes from ADL 01 to ADL 08, and the ninth class includes the seven falls. A graphical representation of the roc auc curve is shown

TABLE 9. Multiclass classification results of the machine learning model and applied sensor. The roc auc-score, overall accuracy, F1-scores, and MCC ± se.

model	metric	Acc_8g	Acc_16g	Gyro
kNN	roc auc-score	0.909±0.0120	0.916±0.0091	0.827±0.0072
	accuracy(%)	79.23±0.966	80.72±0.786	65.82±1.198
	F1-score(%)	57.31±2.056	60.43±1.680	38.47±0.254
	MCC(%)	72.08±1.239	74.14±0.999	53.03±1.348
SVM	roc auc-score	0.990±0.0034	0.991±0.0019	0.975±0.0065
	accuracy(%)	83.46±1.076	83.94±1.172	73.20±1.510
	F1-score(%)	73.96±2.245	74.83±2.138	61.83±2.054
	MCC(%)	81.41±1.150	81.83±1.122	70.46±1.779
ANN	roc auc-score	0.813±0.0419	0.933±0.0100	0.832±0.0247
	accuracy(%)	53.86±0.886	66.33±3.719	49.94±0.964
	F1-score(%)	11.17±1.941	32.53±5.491	6.55±2.133
	MCC(%)	27.97±1.931	51.79±6.863	13.93±8.105

(A) Twenty-class classification problem using benchmark dataset (SisFall)

model	metric	Acc_2g	Acc_16g	Gyro
kNN	roc auc-score	0.962±0.0064	0.956±0.0054	0.898±0.0067
	accuracy(%)	86.05±1.345	85.18±0.993	76.73±1.170
	F1-score(%)	77.15±1.845	75.40±1.729	62.45±0.832
	MCC(%)	81.53±1.488	80.37±1.281	68.97±1.188
SVM	roc auc-score	0.981±0.0004	0.988±0.0007	0.975±0.0047
	accuracy(%)	81.89±0.674	85.45±0.752	78.58±1.582
	F1-score(%)	80.43±0.683	84.38±0.561	75.54±1.554
	MCC(%)	79.89±0.760	84.21±0.715	75.39±1.509
ANN	roc auc-score	0.980±0.0048	0.976±0.0104	0.942±0.0172
	accuracy(%)	85.29±2.236	83.85±3.499	76.26±4.018
	F1-score(%)	75.77±3.160	72.91±5.476	60.69±6.501
	MCC(%)	80.53±2.657	78.68±4.168	68.37±4.719

(B) Nine-class classification problem using proposed dataset (SNU_Ag_Fall&ADL)

Note: Underlined results represent the best performance of machine learning model.

in Figure 8, Class 0 to 7 are ADL01 to 08 and Class 8 is Falls. Figure 9 shows a comparison of classification performance metrics with kNN, SVM and ANN classifier on proposed dataset using 16 g acceleration sensor.

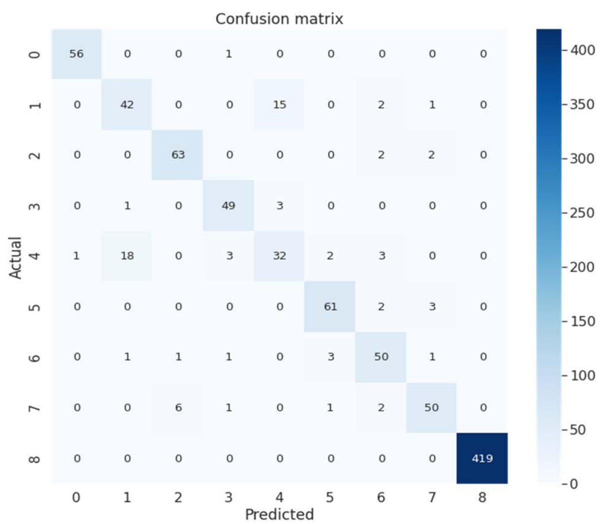

FIGURE 7. Confusion matrices for the nine-class classification (ADL and fall) for the SVM classifier using 16g acceleration sensor.

V. DISCUSSION

The acceleration and angular speeds of falls were observed to be significantly higher in elderly people than in young subjects [52]. The subjects fell onto a mattress; hence, this environment may be different from the actual agricultural environment in which elderly people fall. However, these experimental conditions were considered to be within an acceptable range according to the results of previous studies [49], [50]. The threshold-based fall detection technique is widely used owing to its advantages of low computing complexity and low computational volume [51]. This indicated that the horizontal-plane component can be a useful classification metric for distinguishing between falls and normal agricultural ADLs. MCC was used as a classification performance index to evaluate the disproportionately distributed data. MCC is a classification performance evaluation measure for comparing the accuracy and determining the predictive reliability of unbalanced datasets [53]. In Fall&Ag_ADL_M_Es, the ratio of fall to non-fall data was set at 40:60, which is different from that of the benchmark dataset, namely, 49:51, which does not include elderly data. Although the balanced distribution of data samples is a factor that can affect the analysis results, excellent results were derived from the performance metric in fall &Ag_ADL_M_Es [54]. These results show the possibility that this dataset can also be extended and used to compare and analyze such as imbalanced datasets measured at actual agricultural workplaces in future work. As shown in Figure 7, the confusion matrices ADL02 and ADL05 are interpreted as misclassification due to the similarity of motion between the two tasks. In addition, the roc auc-curve results show that the Class 1 (ADL02) and Class 4 (ADL05) scores were also below the macro average (0.984) in figure 8. In the roc auc-score, all classes can be considered over 0.95 roc auc-score. However, class 1 and 4 are significantly lower than other class groups using one-way ANOVA with Tukey's HSD post hoc test.

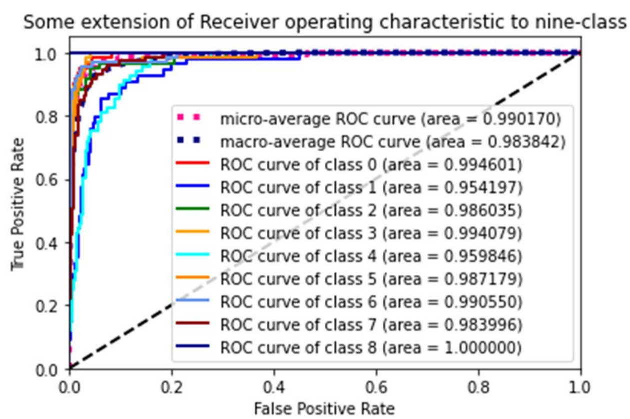

FIGURE 8. Receiver operating characteristic for the nine-class classification (Fall and ADL) for the SVM classifier using the 16 g acceleration sensor.

In multi-class classification analysis, the number of data samples from the proposed fall-mimicking experiment was intentionally controlled. In ADL01–ADL08, fall and ADL data corresponded to 6.67% and 46.6%, respectively, of the total. The binary classification model and generated models were evaluated through performance comparisons of the roc auc-score. The performance metrics reached 0.988 roc auc-score, 85.45% overall accuracy, 84.38% f1-score, and 84.21% MCC on the proposed dataset, respectively. The SVM classifier using 16g acceleration was assessed to show the best performance in multi-class classification problems. It was confirmed that the statistical significance between proposed and benchmark datasets is shown in figure 6. In the case of the multi-class classification problem, statistical significance was observed with the classifiers (kNN, SVM, and ANN), and these statistical tests were confirmed through the results of one-way ANOVA with Tukey's HSD post hoc tests, shown in Figure 9. The overall accuracy using nine-class classification were no significant differences between classifiers (kNN, SVM, and ANN).

In the SVM classifier, Fall&Ag_ADL_M_Es showed higher reliability than the benchmark datasets (Table 9) on the classification of falls and agricultural activity recognition. The proposed model is reliable, even though the data distribution is unbalanced. This indicates that it can also be used to design a classification model for motion recognition. In practice, it can be difficult to record a realistic fall database using elderly volunteers in their actual living environments, especially in rural areas. Therefore, effective fall-mimicking experiments using database models, such as the machine learning approach, are important. In the design of an experimental protocol with an inevitably unbalanced dataset, in addition, the approach proposed in this study is expected to be useful in detecting falls that generate high risks in everyday environments, including falls and agricultural activities.

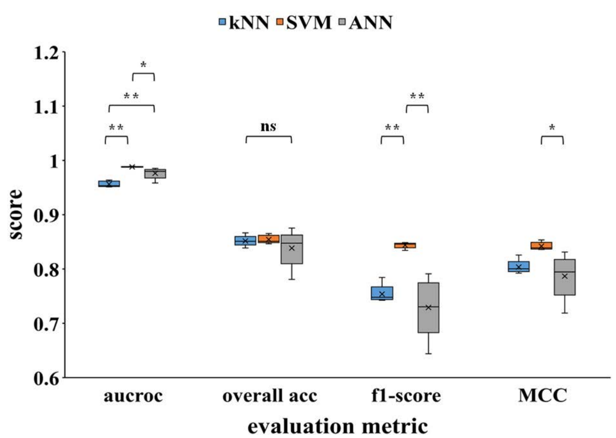

FIGURE 9. Comparison of classification performance metrics with proposed dataset using 16 g acceleration sensor. (Statistical analysis using ANOVA with Tukey's HSD post-hoc test. *p < 0.05, **p < 0.01, ns: not significant, independent treatments: $k = 3$.)

VI. CONCLUSION

The SNU_Ag_Fall&ADL dataset was established by measuring possible fall movements and daily activity data during agricultural work using machine learning approaches (kNN, SVM, and ANN) for the 40 study participants.

Because the experiment was conducted in a limited laboratory setting, it is expected that the classification performance will be affected when the model is applied in the field, namely, in an agricultural work environment. If various age groups were to be included among the experimental participants, especially if the proportion of elderly participants was to increase, the range of motion deviations, such as movement speed, would increase, which could affect the recognition rates of motion [18]. Therefore, future studies should carefully consider participants of various age groups, particularly elderly workers in rural areas, in real agricultural environments during the experimental design process.

This study delivered a valuable result that can be used for machine-learning classification, such as analyzing the relative differences between sensor characteristics using agricultural mimicked data and selecting parameters to improve the classification performance in the future. It is considered that it would be necessary to apply advanced methods to improve the performance, likely in the experimental design, to increase the size of the sample and to improve the analysis of data. Recently, cross-application in various fields has been recommended in the field of data science. For these approaches, in combination with computerized ergonomics in agricultural biomechanics and across all cultures, changes in the disclosure and sharing of results are required to standardize the data and analysis tools available in various fields.

Previous studies aimed to focus on the high prediction performance of fall and nonfall classification initially. Through this study, it was delivered that not only the performance of the benchmark fall classification model was exceeded in binary-class classification but also the reliability of the corresponding model was a high performance for each ADL activities classification. In the future, we plan to focus more on the classification of agricultural work using experimental data measured at actual farm work. Moreover, we plan to consider various methods such as deep learning (CNN, LSTM, or ensemble) models among machine learning techniques. In such machine learning research, omnidirectional analysis and conclusions can be drawn depending on which dataset is used, how the data frame has consisted, and which evaluation metric is used. Therefore, it is necessary to continuously make efforts to present experiments under various conditions in detailed explanation in future research.

If the technology and algorithm implemented in this study are embedded in a portable device or smart accessory, elderly or vulnerable users could be monitored in real-time while connected to an ambient network. This would increase the effectiveness of medical treatment for immediate emergency response and real-time monitoring, thereby improving the quality of life of users who are exposed to accidents such as falls and have positive economic effects by reducing medical expenses. In addition, this study is expected to bring about a large change in the ergonomic approach to agricultural production technology in the era of the 4th industrial revolution and smart farms.

The conclusions that were drawn from this study are as follows:

1. In the threshold-based analysis derived in this study, the classification accuracy of S2 sensors with a wide range of measured values was higher than that of other sensors, as reported in previous studies.
2. In the binary-class classification using machine learning, the proposed model showed improved classification performance. Especially, the ANN classifier showed the highest classification rate and statistically significant differences between the proposed and benchmark datasets.
3. In the multi-class classification model of datasets collected through agricultural fall-mimicking experiments, the performance of the SVM classifier using a wide range of acceleration sensors (±16g) was higher than that using the others. It misclassified some movements such as ADL02 (ladder ascending and descending) and ADL05 (tractor riding and getting off). To improve this misclassification rate, solutions through the application of advanced machine learning models will be addressed as future research topics.

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