A Feasible Fall Evaluation System via Artificial Intelligence Gesture Detection of Gait and Balance for Sub-Healthy Community-Dwelling Older Adults in Taiwan

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ABSTRACT In Taiwan, falls are one of the major causes of permanent disability and seeking medical care in older adults. One in seven people in the Taiwanese population exceeds the age of 65 years, and there are roughly 4 million community-dwelling older adults. One in six older adults have fallen or been diagnosed with Sarcopenia, which can lead to a loss of mobility. The major identified risk factors are impaired balance and gait. Implementing an early-stage prevention system is already an urgent requirement. The primary objective of this study is to propose an artificial intelligence (AI) Internet of Things (IoT) program and to develop an easy-access fall prevention system. This study took the criteria of the Asian Working Group for Sarcopenia (AWGS) and implemented it in field practice. Field experts reviewed data from the combination of gait parameters and gesture parameters and adaptively modified the training course bi-weekly. With 3 months of field practice and intervention, sub-healthy older adults’ average increase in gait speed was 29.83% for male participants and 34.06% for female participants. The results of this study demonstrate that rehabilitation of older adults can significantly improve mobility. This helps to understand the relationship of gait and gesture patterns to walking stability and strategies and adaptive interventions that could be taught in expertise programs to minimize the risk of fall.

INDEX TERMS Artificial intelligence, Internet of Things, health promotion, physical performance, long-term care, sub-healthy aging, fall, Asian working group for sarcopenia.

I. INTRODUCTION Sarcopenia is a geriatric syndrome that is characterized by the progressive loss of skeletal muscle mass and function with age and is associated with increased risks of falls, physical disability, poor quality of life, and mortality [1]. In addition to these adverse health outcomes, recent systematic reviews revealed that the approximately 10% of older adults who have sarcopenia [2] could contribute to economic and societal burdens. In particular, it is worth noting that with the increase in the global older adult population [3], rates of sarcopenia are expected to increase significantly in the world [4]. Therefore, to prevent increased rates of sarcopenia, there is an urgent need to design effective preventive strategies or programs that can be incorporated in people’s daily lives [5].

In older adults, falls are the most prominent external cause of unintentional injury. Research found that one-third of community-dwelling people aged 65 years and older fall each year and that almost half of them experience recurrent falls [6]–[9]. Incidents of falls by older people are strongly associated with hospitalization, severe functional decline, care dependency and early admission to institutional care [10]. Nearly 15% of falls result in non-fatal injuries [11], ranging from minor bruises and wrist lacerations to hip fractures [12]. Notably, 23-40% of injury-related deaths in older people are related to falls [13].
The risk factors for falls are complex and multifactorial in nature. Evidence from longitudinal studies suggests strong interactions among multiple risk factors, such as age, sex, previous history of falls, chronic diseases and environmental factors [11], [13]. Medical conditions that increase the risk of falls include orthostatic hypotension [6], [8], musculoskeletal disease [7], [14], visual impairment [15], [16], low systolic blood pressure, stroke, cognitive impairments, Parkinson’s disease, gait disorders, balance disorders and sensory impairments [2], [8], [16]. Medications in general, and, particularly, polypharmacy increase the risk of falls in older people [17].

In recent years, there has been increasing interest in the impact of research and public health policy on falls. The effectiveness of single and complex programs for the prevention of falls and fall-related injuries was extensively tested among older people at risk of falls [18]. In [18], the evidence for fall prevention interventions for community-dwelling older people at risk of falls was summarized to inform the recommendations provided in the full Integrated Care for Older People (ICOPE) guidelines. Per the guidelines, older adults should be evaluated with a timely diagnosis tool and general benchmarks. In this study, the evidence for fall-prevention interventions will be proved with popular methods such as Instrumental Activities of Daily Living (IADL), Activities of Daily Living (ADL), Timed Up and Go (TUG), grip strength (GS), and Sit to Stand. Despite a simple and short period evaluation, we acquired sufficient of information to evaluate mobility and balance of older adults.

Previous studies have highlighted that there are multiple risk factors for sarcopenia including individual factors (i.e., advanced age, single marital status, low income, and the presence of comorbidities), physiological factors (i.e., body mass index and blood pressure) [19] and lifestyle risk factors (i.e., smoking, lack of physical activity, and malnutrition) [20]. Therefore, it is important to design a comprehensive program for monitoring older adults’ physiological profiles and physical function, as well as promoting healthy lifestyle behaviors in their everyday life. A convolutional neural network (CNN) was applied to realize the fault identification of series arc faults. However, due to the complex network and the deep-learning structure, hyperparameters were challenging to select and adjust.

The goal of this study is to develop a solid mechanism for predicting fall risk for older adults while reserving valuable medical resources. While gathering gait parameters, we categorized velocity and mathematics and converged the models using machine learning. The major difference between the proposed scheme and [16] is the modification of the OpenPose program to a fixed version. Moreover, this study will capture the front and back sides of older adults, instead of the traditional side capture protocol, which is much easier and requires less modification for filtering noise and preserving computing capacity. Such adjustment could help to evaluate mobile balance with adaptive intervention in advance. To be more appropriate for field applications, this study will use 17 points instead of 15 points as validated by field experts. Changing the default setting helps to improve the performance of the F1 score and area under the curve. In addition, this study provides intervention with field expertise for three months. In summary, the major advantages of this study are as follows: (1) Using a front and back capture mechanism, we can observe more detail that can be used to strengthen older adults’ mobile balance and save more computing resources compared to the traditional side capture protocol; (2) combining field expertise with adaptive intervention shows significant improvement and feasibility in comparison to previous research [18]; and (3) the results obtained from this study provide clear benchmarks to improve group fall prevention in long-term care.

The present study is structured as follows. Following the introduction, Section II describes the methodology of gait pattern analysis techniques for sarcopenia and fall prevention. Moreover, the dataset and preprocessing are necessary. Most importantly, the kinematic theory of rapid human movements and its sigma lognormal model are also included. Section III describes the construction and dataset. Section IV elaborates on the experimental setting, flow, and execution details. In addition, experimental results and a pure pattern recognition perspective are provided. Section V describes the comparison review and discussion. In summary, Section VI presents some conclusions and future research directions.

II. METHODOLOGY

Gait is the most commonly assessed daily physical action. The most popular method for gait assessment is the Timed Up and Go (TUG) test. With easy access to measurements, we could easily identify abnormal gait using the Asian Working Group for Sarcopenia (AWGS) criteria. It is very important for long term care if we could proactively recognize and assess abnormal gait to alert caregivers to early warning signs of falls and provide a proper intervention program for gait improvement. The gaits patterns in [21] showed significantly abnormal patterns for recognition perspective. Machine learning implemented on gait-manifested patterns demonstrated the importance of quantitative gait analysis in clinical diagnosis. From this perspective, this study uses spatial-temporal features in discriminating subjects with low-risk from high-risk of sarcopenia. Then, we can derive the important parts including the trajectory of hip, knee and shoulder motion for gait analysis. Moreover, it requires further application of database construction, data preprocessing and related algorithms.

A. SENSORS FOR DATABASE CONSTRUCTION

From the start, the utility of the monitor is eventually for the analysis of health as it changes throughout the day, the week, or even longer. Thus, there is no immediate feedback from all the sensors. The data can help to understand whether subject status was stable or changed over a long period of time. The monitoring over different time periods and the application to health are more intertwined. In general, the categories for the data construction of five sensory are summarized in Table 1,
TABLE 1. Type of sensors for data construction.

| Model                | Description                                                                 | Feature extracted                  |
|----------------------|-----------------------------------------------------------------------------|------------------------------------|
| Optical motion capture| Optoelectronic module would capture motion data                             | Behavior detection and judgement    |
| Wearable sensors     | Accelerometer, Gyroscope, Magnetometer, etc. embedded in chipset to acquire versatility of data | Biomedical aggregation             |
| Doppler              | RF based, capture data by doppler-shifted frequency to identify              | Behavior detection and judgement    |
| 2D/3D Cameras        | Vision based, capture video information by frame and resolution             | Behavior detection and judgement    |
| Floor Sensors        | Pressure based, acquire data by symmetric pressure pads                     | Fall detection, foot tracker, and fall prediction |

where a 2D camera was used as the long-term developing tactic due to popularity of cell phone cameras.

**B. DATA PREPROCESSING**

Generally, we aim to minimize the noise interference for data processing. To be more precise, measurements for camera distance are set by the tester and the Internet of Things (IoT) pad proportion occupation to ensure all testing models use the same criteria. For future expansion to more community-dwelling older adults, it is set to user-friendly so older adults could easily calibrate the camera distance as shown in Fig. 1.

**FIGURE 1.** Camera setting for video capture.

While spatial-temporal features could be fully measured with the fixed dimension of a validation test jig, we can also derive the distance and mutual proportion relations using time and coordination of video or pictures for speed and distance variations. This study applies the line detection by video for speed measurement instead of a traditional stopwatch. Resolution could up to 0.1% and 24 frames per second (FPS). The video setting is shown in Fig. 2.

The gait analysis starts when the tester triggers the line detection by crossing the borderline with his or her foot. Passing the second line will activate the end signal to stop counting. Then, we shall acquire full data via video and frame analysis. Compared with a traditional stopwatch, a trained tester is unnecessary, and the accuracy is increased as well.

**C. RELATED WORKS**

A convolutional neural network (CNN) is well recognized for extracting complex spatial and temporal features. Pose and gesture estimation have been adopted to identify individual movements and trajectories in [22], where the F1 binary score could achieve 0.906. Moreover, the K-nearest neighbor (KNN) algorithm could help to analyze the silhouette change over time with a camera module [23], which uses a vision-based cost-effective framework. However, the performance of such an approach needs improvement due to the limited area coverage. In addition, the support vector machine (SVM) in [24] was constructed with complex features of the means and variances with three axes acquired from the hip-mounted accelerometer. Comparisons in previous research revealed that machine learning-based fall detection methods have better overall performance than threshold-based algorithms. The SVM proof is superior to other combinations, especially its sensitivity and specificity.

**D. KINEMATIC THEORY OF RAPID HUMAN MOVEMENTS**

Using domain knowledge of kinematic theory is intuitive for any rapid human movement. This study utilizes the movements of shoulder, hip, and knees to generate the combination of primitives. Features of velocity and acceleration profile are lognormal [16].
Decades of research led to the sigma lognormal model. It has already been applied to neuromuscular interactions that occur due to rapid movement in a variety of applications and studies [25]. Thus, the sigma lognormal model is also extended to this study. The sigma lognormal model can be represented as

\[
\tilde{v}(t) = \sum_{j=1}^{N} D_j \cos \psi_j(t) \sin \phi_j(t) \Lambda(t; t_0, \mu_j, \sigma_j^2)
\]

where \( j \) is the velocity profile of each stroke; \( D_j \) is the length of the movement; \( t_0 \) is the time-shifted by the time activate of the command; \( \mu_j \) is the log-time delay; \( \sigma_j \) is its log-response time. The velocity profile of a complex movement is given by the following time superposition of lognormal:

\[
\tilde{v}(t) = \sum_{j=1}^{N} \frac{D_j}{\sigma_j(t - t_0)\sqrt{2\pi}} \exp\left(-\frac{(\ln(t - t_0) - \mu_j)^2}{2\sigma_j^2}\right)
\]

where \( \theta \) and studies [25]. Thus, the sigma lognormal model is also occur due to rapid movement in a variety of applications. It has already been applied to neuromuscular interactions that

The interaction and coupling of neuromuscular systems results in sequential complex movements. In this study, the left- and right-angle difference of knee, hip and shoulder trajectory are evaluated. The kinematic theory is helpful for further describing major variations in features. Using periodic validation, we can record and analyze a variety of parameters and accumulate group and individual trends. It is important to converge features and derive insight.

### III. DATASET CONSTRUCTION AND DESCRIPTION

According to consensus with Taiwan Health Promotion Administration, sub-healthy is defined as older adults whom at least has one chronic disease with ambulatory. With bi-weekly periodic tracking and recording for 3 months, 960 videos were eventually obtained. A total of 160 subjects were divided into two equal groups (experimental and control) with 80 sub-healthy subjects each. 102 subjects were female, and 58 were male. The control group and the experimental group participated in physical activity courses for 12 weeks. The control group received traditional courses and measurement only. The experimental group received adaptive course improvement and interventions using periodic gesture parameters measurements. Such data and interactive stimulation help field physical activity trainers contribute solid results.

The videos were made as subscript guidelines as shown in Fig. 3. From the video recording point of view, the tester walked from front to original spot. Validation criteria are aligned with the AWGS requirements. In this study, Timed Up and Go (TUG) and hand grip strength (GS) were used as measurements.

### IV. EXPERIMENT AND IMPLEMENTATIONS

#### A. STUDY PARTICIPANTS

In this study, the participants can be categorized as older adults, health promotion manager, field executor, trainer, artificial intelligence (AI) insight analyzer or joint domain experts. The number of cross-domain participants is summarized in Table 2.

| Category                          | Amount | Definition/Description                                                                 |
|-----------------------------------|--------|---------------------------------------------------------------------------------------|
| Older adults                      | 160    | Age: 65+, 58 male and 102 female, sub-healthy                                         |
| Trainers (National certified)      | 8      | Physical activity instructors of older adults (Domestic License certified)             |
| Health promotion managers         | 3      | Engage and tacit observers (Domestic License certified)                                 |
| Field executors                   | 8      | Record and sustain                                                                     |
| AI insight analysts               | 3      | Engineers for algorithm, coding and parameter analyses                                  |
| Joint domain experts              | 8      | Expertise group includes health promotion (behavior, strategy), nursing (pre-medical), |
|                                  |        | gerontotechnology (technology development), AloT (data insight), nutrition (education and diet consultant) |

#### B. EXECUTION AND PREPROCESSING

The joint execution pattern flow is depicted in Fig. 4. This study compared community-dwelling older adults and the AWGS using validation criteria.
In Fig. 5, both GS and gait speed are considered for alert and periodic tracking parameters. Walking speed consideration are categorized as the benchmarks as concluded from several studies and shown in Fig. 6. When walking speed is under 1 m/s, the risk of falls and developing sarcopenia is increases.

Each recorded parameter was reviewed by a field expert bi-weekly to adaptively modify the training course and to check data on the experimental group. Moreover, videos were acquired by cell phone. Then, the initialization model would recognize individuals. The proposed AI gesture and body pose estimation in this study would establish trajectory by recognition and learning model. The system concept operated as shown in Fig. 7.

For the task of gesture and pose estimation, the OpenPose algorithm was modified for use in this study. Three major unique features were modified as follows:

A. Detection points recorded the trajectories of shoulder, hip and knee.
B. The interpolation for non-detection points and moving average was implemented for blind points.
C. The derivation of the movement balance and the construction of a central line were used to evaluate the bias of body core.

The proposed system would detect older adults’ gestures or poses by video frame-by-frame. Moreover, the modified OpenPose algorithm identified moving objects and plot dots with vector and recorded the trajectory by constructing a

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**FIGURE 4.** Joint execution flow with TA/IoT pattern.

**FIGURE 5.** Define of sarcopenia from AWGS.

**FIGURE 6.** Competitive walking speed with capability model.

**FIGURE 7.** Skeleton AR AI trace statistic validation system pattern.

**FIGURE 8.** Pattern clustering flow based on 6D index.
trapezoid shape for further evaluation as shown in Fig. 9. When using OpenPose [26], [27], no calibration phase is required for the gesture estimation. In addition, it sets 4-in-1 film record to optimize film utilization rate. In addition, it configures as 17 points to focus on filed applications. The category is listed in Table 3.

**TABLE 3.** Type of AI gesture acquire data pattern.

| Model | ID Description               |
|-------|------------------------------|
| Head  | Nose                         |
|       | Eye: Left, Right             |
|       | Ear: Left, Right             |
| Body  | Shoulder: Left, Right        |
|       | Hip: Left, Right             |
|       | Knee: Left, Right            |
|       | Elbow: Left, Right           |
|       | Wrist: Left, Right           |
|       | Ankle: Left, Right           |

Since walking is a continuous and harmonious movement, a threshold value and positioning points are established to distinguish the body portion and activate the recording system as shown in Fig. 2. The measurements of the frame ordinate components (x and y) with the line detection activate the interval defined by the starting and ending detection. In this way, it can minimize the acquisition or isolation. Fig. 10 shows an example of this operation.

**C. SIGMA LOGNORMAL EXTRACTION**

As for the 2D extraction, it can have 3D projection onto the 2D plane. Even though the trajectory has slope and angle, which are correlated to the time domain, it can still rotate coordination using the given x-axis and y-axis as projection. This study evaluates the variations of each move over time and distinguishes between back-and-forth walking. For each move, all the frames are composed of the accumulated trajectory and parameters. Then, after all the data are recorded, the time series contains 3 statistical measures, including the mean, median, and standard deviation. Such statistical measures could conclude normalization before classification. In addition, they can classify modeling time series of joint coordinates of trajectory.

According to previous research [15], [16], [18], [21] and domain applications, sigma lognormal features provide comparative advantages to other features. Thus, sigma lognormal features were directly adopted into the proposed algorithm to verify the corresponding results. With 160 older adults and 6 times recorded for each adult, a total of 960 videos were assessed to create the database. Then, the database containing sigma lognormal features was restructured as well. All the body position points were recognized by order with nose, eye, ear, shoulder, hip, knee, elbow, wrist, and ankle sequentially.

**D. CLASSIFIERS AND SETUP**

The classification was performed with K-fold cross validation with 6:4 proportion and divided into 8 categories using the older adults’ personal profiles. With configured data, ensemble techniques can be achieved by defining out of band elements to be correlated. Four common classifiers including the K-nearest neighbor (KNN), random forest, AdaBoost with decision tree as base learner, and linear support vector machine (LSVM) were adopted to compare data in this study.

In this comparison, the KNN is configured with the 5 nearest neighbors. Moreover, it applies 50 decision trees and uses the maximum depth of 5 to minimize overfitting for the random forest classifier. In addition, the AdaBoost holds 10 decision trees and each learner has a maximum depth of 10. Furthermore, the C parameter related to margin separating hyperplane in the LSVM is selected as $C = 1$. The training hardware is equipped with GPU Nvidia GeForce 2080 and 8G DRAM.

**E. RESULTS**

Relevance to field application is the core value of this study. It has to be validated by both accuracy and real-time demonstration. Accuracy is defined as precise match point onto gesture without mismatch or overfitting that causes bias or misleading. The joint state-of-art comparisons can be found in Table 3 in [28]. While a higher accuracy may result from a heavy computation resource, it can be hard to provide...
simultaneous information feedback. Prompt response time and light computation may sacrifice accuracy as concession. In this study, a total of 17 points for AI gesture parameters with continuous frame recognition would need to be observed by physical activity trainers. Different algorithms and testing results are summarized in Table 4, where F1 score, sensitivity, specificity, precision, mean accuracy, and area under curve (AUC) are compared. While accuracy is under 95%, accumulated trajectory would cause mismatch when using the naked eye. Some of the testing algorithm gestures have over 95% recognition as seen in Table 4.

Real time is defined as fast feedback to field trainers or older adults without a long queueing period. As for real-time operation, satisfying results could be obtained after the user practiced using the system for 1 hour with real-time inference feedback. Only LSVM has the shortest computing period among most common classifiers. Consequently, the obtained results from the proposed data preprocessing helps accelerate training and increase classification accuracy while using LSVM. This would be tremendous progress for older adults and field trainers who could get immediate feedback to move forward, an appropriate implementation demonstrated in real-time, and a faster computing update time. While the LSVM has advantages compared to other algorithms, it provides the sigma lognormal for further comparison before the implementation of the proposed algorithm in practice. The corresponding comparative results are given in Table 5.

TABLE 4. Different algorithms and testing results.

| Algorithm   | F1  | Sensitivity | Specificity | Precision | Mean Accuracy | AUC   |
|-------------|-----|-------------|-------------|-----------|---------------|-------|
| KNN         | 0.938 | 0.932       | 0.965       | 0.971     | 0.950         | 0.951 |
| Random Forest | 0.942 | 0.943       | 0.955       | 0.957     | 0.943         | 0.955 |
| Ada Boost   | 0.923 | 0.942       | 0.955       | 0.967     | 0.942         | 0.940 |
| LSVM        | 0.962 | 0.932       | 0.952       | 0.969     | 0.953         | 0.965 |

TABLE 5. Comparisons of LSVM with and without sigma lognormal.

| Algorithm                        | F1  | Sensitivity | Specificity | Precision | Mean Accuracy | AUC   |
|----------------------------------|-----|-------------|-------------|-----------|---------------|-------|
| LSVM with sigma-lognormal        | 0.945 | 0.972       | 0.935       | 0.957     | 0.950         | 0.951 |
| LSVM without sigma-lognormal     | 0.948 | 0.963       | 0.945       | 0.957     | 0.948         | 0.947 |

The LSVM with sigma lognormal features is extended into the proposed motion identification. With 3 months intervention and supervision by field physical trainers as the adaptive foundation, the experimental group showed significant progress compared to the control group. The major reason is because it can be easier for experts to observe the bi-weekly video and data pattern trend simultaneously. It is convenient for experts to refresh their interventions for the experimental group by reviewing data and pattern accordingly. Moreover, females show more interest in their body shape and gesture while males prefer to enhance their strength. These preferences also reflect on their testing results. Pre- and post-testing results were evaluated using the AWGS gait speed and grip strength as shown in Figs. 11-14. The walking speed progress after 3 months of adaptive intervention for male and female are depicted in Figs. 11 and 12, respectively. In addition, Figs. 13 and 14 depict the grip strength progress after 3 months of adaptive intervention for male and female, respectively. The average gait speed improvement in the experimental group is 30.6% compared to 14.8% in the control group. The average grip strength improvement in the experimental group is 1.5% compared to 0.9% in the control group.
V. COMPARISON AND DISCUSSION

In 2019-2020, the AWGS considered 400+ elements of AI programs that indicate simpler and highly related factors to observe frail and prediction variables of older adults. The strongest indication for community-dwelling older adults is to focus on gait speed and handgrip strength for easy implementation. To be more prudent, plenty of meetings with the Taiwan Health Promotion Administration were arranged and the recommendations from the AWGS were approved and certified. Our goal is to define a general formula for community-dwelling older adults that focuses on prevention to ease the pressure of the aging crisis in Taiwan and east Asia. Where there are plenty of parameters we could have proposed, we concentrated on using recognized parameters for the target audience to validate our intervention: sub-healthy older adults and field feasible items to achieve government execution track.

There is no doubt that medical instruments have the highest precision compared to the naked eye; however, the expense of acquiring medical instruments may block accessibility. Our intention is to utilize an easy-access jig-like cell phone and handgrip meter that can be feasibly used by community-dwelling older adults in the field or in home care. Our AI gesture system could achieve in-band and out-of-band effects for win-win solutions. In-band contributes accurate body data pattern recognition with minimum distortion using our proposed algorithm. Out-of-band could enable real-time response for field physical activity trainers to adapt and individualize the treatment for older adults, which could otherwise not be recognized by the naked eye. Moreover, we could even alert sub-healthy older adults that demonstrate signs of frailty during periodic courses. While both the experimental group and field physical activity trainers are satisfied with new approaches and intervention, we have strong confidence we could benefit millions of Asian sub-healthy older adults with this cost-effective intervention.

For improved physical activity parameters, IoT devices and videos were adopted as user-friendly validation test jig. The results of the compromise contributed to accurate video analysis, which assists field physical trainers in observing personal and group parameters with visualized data and the AI skeleton gesture trajectory. The trapezoid shape helps experts identify the movement balance and promptly identify older adults who are progressing or declining. Moreover, it is important to categorize testers and distribute intervention plans according to their temperament. In addition, a more efficient intervention approach would really benefit older adults.

For the rehabilitation program in this study, the control group and the experimental group participated in physical activity courses for 12 weeks. The control group received only traditional courses and measurement. The experimental group received adaptive course improvement and interventions using periodic AI gesture parameters and measurements. Precision and sensitivity are the keys in reducing bias and recognition onto continuous video image frames. Physical activity trainers could periodically review pattern insights to adaptively modify content with detailed tailor-made adjustments throughout the course. Such data and interactive stimulation help field physical activity trainers contribute solid results. Subscript is an example of a visual that could help easily identify the trajectory and shape. The patterns, as shown in Fig. 15, are provided to enhance the body core strength by shape and response time.

With clear identical benchmarks to proceed, not only did we find pre-frail cases improved, but also the capability of sub-healthy older adults achieved better results than other rehabilitation programs. The average gait speed improvement in the experimental group is 30.6% compared to 14.8% in the control group. The average grip strength improvement is 1.5% compared to 0.9% in the control group. Compare with traditional rehabilitation programs, result is remarkable and superior. All field experts were quite impressed and satisfied with our achievements.

With recent iterative research for older adults, Lee et al. [29] applied a health promotion program for 9 months. The expertise group arranged traditional courses with scheduled activities like aerobic exercise and periodic activity. In [29], it achieved 3.56% improvement for gait speed. Moreover, the
long-term intervention in Japan Unnan city [30], [31] was a 5-year tracking project for older adults. It demonstrated minimal improvement in the first 3 years, but eventually contributed 4.57% improvement in physical activities. With such limited growth, traditional intervention methods may need new approaches as well. Jadczak et al. [32] aimed to determine the effectiveness of exercise interventions, alone or in combination with other interventions, in improving physical function in community-dwelling older people identified as pre-frail or frail. As for [32], it concluded that multiple components of exercise can be recommended, but there is currently no related experimental data provided in [32]. The comparisons with the latest short-term to long-term intervention in [29]–[31] are given in Table 6. Although the performance of the proposed system is clearly superior to the ones in [29]–[31], a three month validation period may not be sufficient to prove the performance of long-term therapy. In the future, it could be beneficial to continuously observe the effectiveness of the proposed system.

### VI. CONCLUSION AND FUTURE RESEARCH

Joint-developing with intervention and parameters analysis onto the proposed user-centric 6 diversify has been successfully used to build a 6 diversify predictable frailty risk estimate recovery substantial system. The resolution/validation accuracy is 97.99% based on 24 FPS using velocity-based, angle-based and sigma lognormal features and video/walk orientation. The sensitivity is 97.2% and helped the video react more precisely. With 160 sub-healthy/healthy older adults receiving 3 months of intervention resulting in AI extractions from 960 videos, the experimental group average improvement of gait speed is 29.83% for males and 34.06% for females. Compared with the Japanese intervention program of pure physical activity training over 3 to 5 years, the average values of gait speed improvement were 1.46% and 4.57% for urban older males and females, respectively [29]–[31]. The promising results may be considered a short-term achievement. However, the visualized data could contribute clear indications for TA/PT to adaptively modify their course with parameters as solid reference. In addition, the proposed system architecture integrated with IoT devices and AI video analysis could replace existing meters and paperwork as more cost-effective and user-friendly for community-dwelling field interventions.

In this study, a successful sarcopenia prevention/alert system was implemented using a structured technology/method to effectively detect and pre-diagnose sarcopenia based on AWGS criteria. In the future, we shall enlarge testing samples and include dementia among the inclusion criteria. Additionally, with an increase in the sample size, the next-stage joint disability prevention/alert system would function in an in-depth manner regarding user-related information, cross-correlation with physical activity parameters, training bias and solution tracing for community-dwelling older adults. With increasing amounts of continuous data and experimental verification, the adaptability of the proposed mechanism would also be relatively strengthened. In future research, the feature extraction method could be optimized to reduce the complexity of calculation, and we would reorganize the distribution of resources for community-dwelling old adults. In addition, benefiting all citizens and the community is the target goal in near future.

### COMPLIANCE WITH ETHICAL STANDARDS

All the design/operation/execution is approved by IRB authority. IRB no. ECKIRB1071204.

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