Automated Prescreening of Mild Cognitive Impairment Using Shank-Mounted Inertial Sensors Based Gait Biomarkers

AHSAN SHAHZAD1, (Member, IEEE), ARESH DADLANI2, (Senior Member, IEEE), HYEONIL LEE3, (Student Member, IEEE), AND KISEON KIM4, (Life Senior Member, IEEE)

1Department of Computer and Software Engineering, National University of Sciences and Technology, Islamabad 44000, Pakistan
2Department of Electrical and Computer Engineering, Nazarbayev University, Nur-Sultan 010000, Kazakhstan
3Korea Automotive Technology Institute, Icheonam, Yeonggwang 57063, South Korea
4School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology, Gwangju 61005, South Korea

Corresponding author: Ahsan Shahzad (ahsan.shahzad@ceme.nust.edu.pk)

This work was supported in part by the GIST Research Institute (GRI), Gwangju Institute of Science and Technology (GIST), South Korea.

ABSTRACT The mild symptoms in Mild Cognitive Impairment (MCI), a precursor of dementia, often go unnoticed and are assumed as normal aging signs. Such negligence result in late visits which consequently, lead to the diagnosis and progression of dementia. An instrumented gait assessment in home settings may facilitate the detection of subtle MCI-related motor deficits thus, allowing early diagnosis and intervention. This paper investigates potential gait biomarkers derived from shank mounted inertial sensors signals under normal and dual-task walking conditions using data collected from thirty MCI and thirty cognitively normal (CN) subjects. To identify potential gait biomarkers for MCI screening, we assess the variance and predictive power of each feature. Moreover, multiple classification models using different machine learning and feature selection techniques are built to automate MCI detection by leveraging the gait biomarkers. Statistical analysis reveal multiple gait parameters that are significantly different under both single and dual-task settings. However, we show that dual-task walking provides better distinction between MCI and CN subjects. The machine learning model employed for MCI pre-screening based on the inertial sensor-derived gait biomarkers achieves accuracy and sensitivity of 71.67% and 83.33%, respectively.

INDEX TERMS Mild cognitive impairment, dementia, gait analysis, inertial sensors, gait biomarkers, early detection.

I. INTRODUCTION

The prevalence and incidence rate of cognitive problems are evident in the growing elderly population worldwide. Dementia is a disorder that is characterized by a decline in cognition involving one or more cognitive domains such as learning and memory, complex attention, language and perceptual-motor. Mild cognitive impairment (MCI), a slight but noticeable and measurable decline in cognitive abilities, has been established as a precursor to the development of dementia. Each year, nearly 10% to 15% of the elderly people with MCI progress to dementia. Alzheimer’s disease (AD) is the most common form that accounts for 60% to 70% of dementia cases and is projected to increase to 115.4 million people worldwide by 2050 [1].

The status quo of detecting cognitive impairments typically rely on clinical assessments that are usually contingent on battery of cognitive tests, questionnaires, and physical and neurological examinations. Difficulties in identifying when assumed signs of aging are, in fact, early disease symptoms, result in late diagnosis. Therefore, MCI screening and early diagnosis is extremely important, preferably under living conditions, in order to diagnose and treat the causative factors and to help prevent or postpone the progression of dementia. This stimulates the research to find novel, inexpensive, and reliable biomarkers for early MCI diagnosis and to facilitate the current clinical diagnosis methods.

With regard to early detection of AD and dementia, there exists an extensive body of research based on physiological
A. Shahzad et al.: Automated Prescreening of MCI Using Shank-Mounted Inertial Sensors

measurements using biological signals (EEG, MEG) [2], neuro-imaging methods (MRI, PET) [3], cerebrospinal fluid (CSF) [4], and blood tests [5]. There however, exist only few reported efforts that utilize behavioral changes for automated detection of cognitive decline [6]. Similarly, not much has been done towards objective gait assessment of MCI people. MCI symptoms are often presumed as normal aging process in elderly people which lead to delayed consultation with the physician. In addition to delayed diagnosis, the high costs associated with disease progression monitoring and expensive neuro-imaging tests are other big concerns. It is thus, of great significance to find non-invasive, unobtrusive, and inexpensive biomarkers to assess cognitive health under normal living environments [6].

In recent years, gait assessment has emerged as a powerful tool in neuro-degenerative diseases that can provide surrogate markers for disease diagnosis, its progression monitoring, and evaluating intervention strategies. Nonetheless, gait is a rather complex cognitive task and is not a simple motor activity independent from cognition [7]. This hypothesis has been recently reinforced by dual-task tests [8]. Identifying MCI-related gait deficits may essentially lead to new insights into early diagnosis of dementia, refine current diagnostic assessments, and establish new preventive strategies. While Parkinson disease and multiple sclerosis (MS) have attracted myriad research attention among neurological gait disorders [9], there exist very few works that analyze the gait of AD patients using inertial sensors [10]–[12]. The authors in [10] measure the gait parameters of dementia people in every day life using triaxial accelerometer. In [11], the authors propose gait and balance analysis algorithms using inertial sensors data for Alzheimer’s patients. However, the algorithm only extracts temporal parameters in a step-by-step manner. More recently, a foot-mounted inertial sensor-based robust gait analysis algorithm was proposed in [12] for non-hospital settings which was validated using pathological gait of different neurological disorders. According to meta-analysis of studies focusing on objective instrumented gait assessment of MCI people, it has been shown that MCI people tend to have significantly different gait speed, stride length, stride time, and coefficient of variation with respect to their cognitively intact peers [13]. Ghoraani et. al. [14] compared the gait of AD, MCI and cognitively normal (CN) people using a computerized walkway system.

To our best knowledge, there exists no automated system reported yet for early diagnosis of dementia through MCI detection in home settings using inertial sensor-based objective gait analysis within a machine learning framework. Moreover, most of the existing works on instrumented gait assessment of MCI people use pressure sensitive walkways (GAITRite system) [14] or video systems [13]. Inertial sensors overcome the limitations of such systems and offer a cost-effective, pervasive, and reliable solution. In this line, the main objectives of this study are to extract and find (shank mounted) inertial sensor-based gait parameters or biomarkers that can facilitate diagnosis/pre-screening of MCI under home environment. Moreover, we use machine learning techniques and gait biomarkers to develop a cost-effective, pervasive, reliable, and automated system for early diagnosis of dementia through early detection of MCI.

To summarize our main contributions, we first provide a comprehensive gait analysis of MCI and CN people under single and dual-task scenarios using wearable inertial sensors. We then highlight the potentials of gait biomarkers for MCI detection through comparison of mini-mental state examination (MMSE) scores. Finally, we propose a machine learning model based on dual-task inertial gait biomarkers for early detection of MCI in home settings.

The remainder of the paper is organized as follows: Section II describes the data-set and preprocessing steps used in our analysis. Section III details the gait parameter extraction procedure. In Section IV, we present the experimental results with discussions. Finally, Section V summarizes our findings and concludes the paper.

II. DATA-SET AND PREPROCESSING

In this section, we discuss the selection and diagnosis procedures of subjects who participated in this research. Then, the inertial sensor data acquisition and pre-processing procedures are detailed, followed by explanation of the experiment protocol.

A. PARTICIPANTS

A total of 60 elderly subjects, comprising of 30 cognitively normal (CN) and 30 MCI-diagnosed participants, were recruited from the pool of individuals registered at the National Research Center for Dementia in Gwangju, South Korea, from October 2016 to February 2018. All the subjects were evaluated and diagnosed by the medical doctors at Chosun University Hospital and Chonnam National University Hospital in Gwangju, South Korea. The study protocol was approved by the Institutional Review Board of Gwangju Institute of Science and Technology (GIST), South Korea. All the applied experimental procedures were carried out in accordance with the approved guidelines and written informed consent was obtained from all the participants or their relatives/caregivers prior to the experiments.

All the participants underwent the comprehensive clinical interview, imaging, and neuropsychological assessments. Their global cognition was assessed using MMSE, and the neuropsychological assessments were performed using Seoul Neuro-psychological Screening Battery (SNSB) [15] which consists of five major cognitive domains, namely attention, language, visuo-spatial, memory, and frontal/executive domains. The brain structure was scanned by magnetic resonance imaging (MRI) and Beta-amyloid (βA) plaques were investigated by positron emission tomography (PET) scans. MCI is determined for those subjects with values higher than or equal to 1.5 standard deviation based on the guidelines provided in [16] and [17]. Subjects showing evidence of focal brain lesions on MRI, dementia other than AD, and any other significant medical, neurological or psychiatric disorders that
TABLE 1. Demographics of Mild Cognitive Impairment (MCI) and Cognitively Normal (CN) subjects.

|                | CN     | MCI    | p-value |
|----------------|--------|--------|---------|
| Subjects       | 30     | 30     | -       |
| Age (yr)       | 74 ± 4.35 | 75.63 ± 2.83 | 0.09 |
| Height (cm)    | 160.5 ± 7.28 | 163.59 ± 8.35 | 0.11 |
| Weight (kg)    | 62.4 ± 7.2 | 63.76 ± 8.19 | 0.19 |
| Gender (M/F)   | 16/14  | 21/9   | 0.0066  |
| MMSE           | 27.77 ± 1.63 | 25.8 ± 3.46 | 0.95 |
| Education (yr) | 10.5 ± 4.7 | 10.57 ± 4.8 | 0.95 |

could affect cognitive functions and gait were excluded from this study.

The subjects were mainly divided into two categories: (i) Cognitively Normal (CN) people with or without βA deposits and (ii) MCI patients mainly due to AD (positive-amyloid) with few MCI subjects with negative-amyloid as well. The demographics and neuro-psychological characteristics of all the participants along with their p-values have been summarized in Table 1. Analysis of Variance (ANOVA) was used to compare the two groups and no significant differences were observed in the age, gender, height, weight, and education level attributes of the two groups.

B. EXPERIMENT PROTOCOL AND INSTRUMENTATION

The experiment protocol consisted of normal or single-task (ST) and dual-task (DT) walking trials performed by subjects wearing inertial sensors on each shank. The subjects were instructed to walk along a straight 10 m walkway, turn around, and come back 10 m to the starting point at their own ‘normal’ walking pace as shown in Figure 1. In the dual-task walking scenario, subjects were asked to perform additional cognitive tasks along with normal pace walking. The two different cognitive tasks considered were (i) down counting (DC) from 70 with decrements of 1, and (ii) speaking out animal names (NA). Though there were no specific instructions to give priority to any task, subjects were asked to try to walk continuously without stopping. However, if a subject made a complete stop during the experiment and started focusing on the cognitive task only, the experiment was repeated. This is because any long pause in walking will result in non-realistic temporal gait parameters.

The wearable Shimmer 3 inertial sensor, composed of a triaxial accelerometer and triaxial gyroscope, was used in this study [18]. The sensors were pre-calibrated using the well-known calibration procedure in [19], and were configured to measure range ±4.0g with sampling rate of 64 Hz. The sensors were attached to the mid-shank of each subject in a way that its x-, y- and z-axes were aligned with the subject’s antero-posterior (AP), vertical (V), and medio-lateral (ML) axes, respectively. During the experiment, the sensors’ data was acquired and transferred over Bluetooth to a nearby laptop and time synchronized data was recorded using the ConsensysPRO Software [20]. An observer annotated the data to highlight the mid 6 m walking distance.

III. GAIT PARAMETERS EXTRACTION

Human gait or walking pattern typically involves repetitive motion; therefore gait signals usually have a pseudo-periodic nature. Hence, the gait pattern can be segmented into cycles or strides and each cycle can be further divided into the swing and stance gait phases with the help of gait events (GEs) defined as follows:

- Toe-off (TO): Terminal-contact or Toe-off or Final-contact is the moment when the foot leaves the ground.
- Heel-strike (HS): Initial-contact or Heel-strike is the moment when the foot lands on the ground after swing to support the body weight.

A. GAIT SEGMENTATION AND EVENT EXTRACTION

In the literature, the two reported approaches for GE extraction are peak detection algorithms ([21] and [22]) and hidden Markov models (HMMs) [23]. A comprehensive comparison of the GE extraction algorithms can be found in [24]–[26]. Besides the different GE extraction methods, [25] also compared the sensor types and their positioning. They reported that GEs are most accurately detected by shank-mounted gyroscope signals. Likewise, we consider shank-mounted gyroscope signals for GE detection in our analysis.

To detect each stride in continuous walking signals, we employ the peak detection approach. The findpeaks function (‘minpeakeheight = 90’) in MATLAB is used to locate the mid-swing peaks in the low pass filtered (8th order Butterworth filter, $f_c = 6$ Hz) angular velocity signals along the z-axis. The low pass filtered signal is used to suppress the sharp spike at HS points and to avoid their detection as new strides. After the detection of each stride, we reduce the search range for HS and TO in each gait cycle in order to find GEs accurately without missing any point. The GE detection algorithm at first identifies the time intervals during which no GE can occur, i.e., trusted swing ($T_{SW}$) and trusted stance ($T_{ST}$) of each limb using the method proposed in [21]. This approach remarkably reduces the time interval ($T_{TO}$, $T_{HS}$) in which HS and TO have to be searched, and consequently, the risk of extra GE detection. Finally, TO and HS are identified as the negative peak and first negative local minimum in $T_{TO}$ and $T_{HS}$ search intervals, respectively.
B. SPATIO-TEMPORAL PARAMETERS AND VARIATIONS

The temporal parameters can be easily calculated in a step-by-step manner with the help of GEs. Each feature is briefly described as follows:

- **Swing Time (s)**: The time duration between the TO and HS gait events of one leg within a gait cycle.
- **Stance Time (s)**: The time duration between the HS and TO gait events of one leg within a gait cycle.
- **Double Support Time (s)**: The phase where both feet are in contact with the ground while walking. Here, synchronization between the nodes becomes critical. This feature however, can be extrapolated using swing time and stance time in each gait cycle (i.e., stance time of one leg minus swing time of the other leg).
- **Stride Time (s)**: The time duration from the HS point to the next HS point of the same foot.
- **Step Time (s)**: The time between the HS point of one foot and the HS point of the other foot.
- **Cadence (steps/min)**: Total number of steps per minute.
- **Swing Period (%)**: The ratio of the swing time to the stride time as a percentage of gait cycle.
- **Stance Period (%)**: The ratio of the stance time to the stride time as a percentage of gait cycle.
- **Double Support Period (%)**: The ratio of the double support time to the stride time as a percentage of gait cycle.
- **Gait Speed (m/s)**: According to [27], the instantaneous or step-by-step gait speed estimation models using inertial sensors can be categorized into three types namely, human gait model, abstract model (machine learning), and direct integration models. Though there exist many different algorithms for gait speed estimation from inertial sensor data, there always exists some error due to noisy measurements, integration drift, and so on. Hence, we focused on conventional or clinical approach to obtain the gait speed parameter by dividing the walk distance (6 m) with time.

C. ANGLE-RELATED PARAMETERS

The shank angle during the gait cycle was measured along the mid-sagittal plane perpendicular to the ground. The zero shank angle represents the instant of foot-flat around mid-swing or mid-swing. A negative value signifies backward rotation around the knee joint while the positive value represents a forward swing rotation around the knee joint with the heel going upward. The mean, standard deviation, minimum and maximum values of shank angle were computed.

D. NON-LINEAR FEATURE EXTRACTION TECHNIQUES

The geometric representation of dynamic system trajectories in the phase plane is called the phase portrait. Typically,
FIGURE 4. Gait variability as measured by total centroid drift of phase portrait cycles.

the position information is often plotted against its first time derivative as depicted in Figure 3. By quantifying this geometric shape, different gait parameters can be extracted. Recently, researchers proposed some new parameters for gait analysis by applying non-linear analysis techniques to phase portrait as given below:

- **Gait Variability**: The gait variability is analyzed using the inconsistency of the phase portrait location between gait cycles throughout the trial. The centroid is calculated as the mean of all (x, y) data points for each gait cycle. Total centroid drift is used as a measure for gait stability and is defined as the path length or total point-wise Cartesian distance traveled by the centroid on the phase plane over the (first) three gait cycles of each trial [28] as shown in Figure 4.

- **Gait Complexity**: The notion of gait complexity leans on measuring the jerkiness of a motion. It is quantified in [28] by the number of harmonic frequencies needed to accurately describe the 2-D shape of phase portrait with Elliptical Fourier Analysis (EFA) [29]. Complexity metric is defined as “the minimum number of harmonics in a reduced-order fit, which was required to eliminate 99.9% of the error between a full-order fit (500 harmonics) and zero-order fit (mean centroid)” [28]. Large number of harmonics indicates greater gait complexity. Figure 5a shows the closeness of full-order fit, estimated using 500 harmonics in EFA, with phase portrait of three gait cycles, whereas a very close approximation of full fit, i.e., reduced fit can be seen in Figure 5b obtained by using 27 harmonics only.

- **Gait Regularity**: In order to assess the variability between the gait cycles, a Poincaré return map or first return map can be used. A Poincaré return map samples a particular event of interest at the same time instant in a repetitive signal. Gait regularity can be defined as the sum of distances from the cluster’s center to all the points [9]. As shown in Figure 6, the shank angle

and acceleration magnitude at the TO and HS points, respectively, were used to compute gait regularity.

IV. RESULTS AND DISCUSSION

In this section, we first present the results for our statistical analysis of gait parameters in order to determine their
efficiency for MCI screening. Then, by utilizing the selected gait biomarkers, different machine learning models have been built and compared for their classification performance.

### A. STATISTICAL ANALYSIS

The ANOVA test was used to find the significantly different gait parameters between CN and MCI subjects. The $p$-values of the gait parameters obtained under different walking scenarios are listed in Table 2. We observe that there exist many significantly different gait parameters between CN and MCI people during both ST and DT walking scenarios. However, the DT scenario increases the discriminative power of gait parameters as they exhibit lesser $p$-values than the ST scenario. Among DT scenarios, DT-NA creates more deterioration in walking patterns of CNs and MCIs as compared to DT-DC, and generates more number of significantly different gait parameters. This observation can also be seen in Figure 7. Further more, the MCI people presented significantly higher temporal features and their variations (swing time, stance time, stride time, step time, CV of stride time, CV of step time), while having lower cadence, gait speed, maximum shank angle in comparison with the CN.

In addition, the predictive power of each feature is measured using the area under the receiver operating curve (AUC).

### TABLE 2. ANOVA results of 23 features extracted from shank inertial signals during single-task and dual-task walking conditions. The bold values represent significantly different features ($p$-value < 0.05). The last column shows area under the ROC curve values of each feature from DT-NA experiment.

| Feature No. | Gait Parameter                          | ST-Walking $p$-value | DT-DC Walking $p$-value | DT-NA Walking $p$-value | AUC    |
|-------------|----------------------------------------|----------------------|-------------------------|-------------------------|--------|
| 1           | Swing Time                             | 0.022524             | 0.008446                | 0.013697                | 0.6567 |
| 2           | Stance Time                            | 0.02011              | 0.003952                | 0.01898                 | 0.6917 |
| 3           | Double Support Time                    | 0.137795             | 0.012415                | 0.074738                | 0.6733 |
| 4           | Stride Time                            | 0.011896             | 0.003264                | 0.009942                | 0.6961 |
| 5           | Step Time                              | 0.013079             | 0.003247                | 0.010186                | 0.6922 |
| 6           | Cadence                                | 0.01376              | 0.003583                | 0.010019                | 0.6906 |
| 7           | Swing Period                           | 0.299833             | 0.103909                | 0.128888                | 0.6356 |
| 8           | Stance Period                          | 0.299833             | 0.103909                | 0.128888                | 0.6356 |
| 9           | Double Support Period                  | 0.24864              | 0.073979                | 0.190587                | 0.6233 |
| 10          | Gait Speed                             | 0.016868             | 0.002813                | 0.002633                | 0.7289 |
| 11          | CV of Swing Time                       | 0.213179             | 0.222785                | 0.011888                | 0.6411 |
| 12          | CV of Stance Time                      | 0.515457             | 0.072578                | 0.092257                | 0.5733 |
| 13          | CV of Double Support Time              | 0.763278             | 0.100174                | 0.949687                | 0.5322 |
| 14          | CV of Stride Time                      | 0.193547             | 0.126608                | 0.01109                 | 0.6589 |
| 15          | CV of Step Time                        | 0.205138             | 0.147762                | 0.011128                | 0.6456 |
| 16          | Shank Angle Mean                       | 0.431087             | 0.492369                | 0.730073                | 0.5461 |
| 17          | Shank Angle std.                       | 0.351592             | 0.182433                | 0.112681                | 0.6406 |
| 18          | Max. Shank Angle                       | 0.188394             | 0.139345                | 0.011651                | 0.7006 |
| 19          | Min. Shank Angle                       | 0.45232              | 0.53807                 | 0.369369                | 0.5933 |
| 20          | Regularity SA at TO                    | 0.120458             | 0.142166                | 0.14339                 | 0.5378 |
| 21          | Regularity AVM at HS                   | 0.504447             | 0.878194                | 0.344745                | 0.5628 |
| 22          | Variability using Centroid Drift       | 0.915626             | 0.442104                | 0.794142                | 0.5583 |
| 23          | Complexity using EFA Harmonics         | 0.815142             | 0.58837                 | 0.80836                 | 0.5494 |

* DT-DC = Dual-Task Down Counting, DT-NA = Dual-Task Naming Animals, ST = Single Task, AUC = Area Under the Curve.

FIGURE 7. CN and MCI people gait parameters comparison under different walking conditions.
TABLE 3. Performance comparison of different MKL-SVM based classification models that are built using various features selection techniques. For each feature selection technique the best performance is listed.

| Models | Performance Measures | Parameter Settings |
|--------|----------------------|--------------------|
|        | Accuracy (%) | Sensitivity (%) | Specificity (%) | FSM | NBF | MKL-SVM |
| M1     | 61.67       | 56.67           | 66.67           | –   | 23 (all) | C = 60 – 300 |
| M2     | 68.33       | 73.33           | 63.33           | Wilcoxon | 9 | C = 60 |
| M3     | 70          | 83.33           | 56.67           | Mutual Information | 4 | C = 60, 70 |
| M4     | 71.67       | 76.67           | 66.67           | Mutual Information | 4 | C = 300 |
| M5     | 70          | 70              | 70              | Eigenvector Centrality | 8 | C = 50 |
| M6     | 66.67       | 66.67           | 66.67           | Correlation | 15 | C = 90 – 160 |

* FSM = Feature Selection Methods, NBF = No. of features used, MKL-SVM = Multiple Kernel Learning Support Vector Machine, C = SVM hyper-parameter.

TABLE 4. Performance comparison of different classification models that are built using various classification (Decision Tree (DT), Random Forest (RF), and Artificial Neural Networks (ANN)) and feature selection techniques. For each feature selection technique, the best performance is listed.

| Models | Performance Measures | Parameter Settings |
|--------|----------------------|--------------------|
|        | Accuracy (%) | Sensitivity (%) | Specificity (%) | FSM | NBF | Hyper-parameter |
| M7-DT  | 66.33       | 70             | 68.33           | Correlation | 6 | Max_depth = 5 |
| M8-DT  | 63.33       | 70             | 56.67           | Mutual Information | 4 | Max_depth = 5 |
| M9-DT  | 68.33       | 66.66          | 70              | Eigenvector Centrality | 5 | Max_depth = 2 |
| M10-RF | 56.67       | 53.33          | 60              | Correlation | 14 | n_tree = 20 |
| M11-RF | 63.33       | 53.33          | 73.33           | Mutual Information | 4 | n_tree = 10 |
| M12-RF | 68.33       | 66.66          | 70              | Eigenvector Centrality | 5 | n_tree = 20 |
| M13-ANN| 58.35       | 56.66          | 60              | Correlation | 14 | layers = 3 |
| M14-ANN| 53.33       | 56.66          | 50              | Mutual Information | 4 | layers = 2 |
| M15-ANN| 60          | 56.66          | 63.33           | Eigenvector Centrality | 6 | layers = 3 |

* FSM = Feature Selection Methods, NBF = No. of features used.

gait template of each subject is also generated by averaging the two instances. Non-gait parameters such as demographics information or cognitive tests scores were not used in the classification models.

For automated detection of MCI, multiple classification models were generated and compared based on different Feature Selection (FS) techniques and hyper-parameter values. The filter type methods were employed for feature ranking, which include Wilcoxon (non-parametric test), Mutual Information (MI), Eigenvector Centrality (EC), and Correlation-based Feature Selection (CFS). The publicly available feature selection library (FSLib) as a MATLAB toolbox [31] and MATLAB function rankfeatures were utilized for implementing the above mentioned FS algorithms. The Leave One subject Out (LOO) cross validation (CV) was used to report the model performance. In LOO-CV, each time one subject is used for testing, whereas the data of the remaining subjects is used for feature selection and model training. The whole process is repeated until all the subjects were tested.

At first, Multiple Kernel Learning Support Vector Machine (MKL-SVM) was employed as the classification technique due to its superior results on inertial sensor data [32]. The linear, polynomial (2nd and 3rd degree), and Gaussian kernels were built using all the features (for further details please see [32]). For each feature selection approach, the best performing MKL-SVM based classification model is reported.
in Table 3. For each feature selection approach, the number of features to be used and value of hyper-parameter (c) of SVM are optimized and the best performance is reported. As sensitivity is the most important measure, M3 model turns out to be the best with sensitivity equal to 83% and accuracy of 70%. Nonetheless, M4 model offers the highest accuracy of 71.67%. Interestingly, both these models are based on MI-FS technique and also use the least number of features (i.e., 4) as compared to other counterparts.

To validate the superiority of MKL-SVM model, other classification techniques have also been evaluated. Table 4 summarizes the best performance of each classification technique with each feature selection method as represented by Models M7-M15. The maximum accuracy obtained here was 68.33% and is achieved by two models namely, M9-DT and M12-RF using eigen-centrality FS method. Upon comparing the results presented in Table 3 and Table 4, we note that the highest accuracy achieved was 71.67% and sensitivity 83.33% using MKL-SVM as classifier with Mutual Information FS criteria. The index set of the four best features selected by Mutual Information FS technique is \{23, 3, 7, 8\} as described in Table 2. The proposed technique is summarized in Figure 8.

In a slightly similar research work conducted in [14], the authors proposed a diagnostic algorithm based on machine learning techniques and gait data for identification of CN, MCI, and AD people in hospital settings. They utilized expensive computerized walkway systems such as Zenomat and GaitRite and their associated software for gait parameters extraction. Three classifiers were built using SVM technique and selected gait features, one for each binary classification (CN/MCI, MCI/AD, CN/AD). The final label (CN, MCI, AD) is assigned through majority voting. The average classification accuracy achieved using 5-fold cross validation was 78%. Nevertheless, these performance values are not directly comparable with the results reported in Table 3 as they consider 3 class problem including AD subjects which are easier to distinguish from cognitively normal people. In general, it is difficult to identify MCI people from CN with extremely high accuracy using gait analysis alone because MCI people exhibit very mild and multi-domain symptoms.

C. FUTURE RESEARCH DIRECTIONS

In this research, gait biomarkers associated with cognitive decline have been identified under single and dual-task walking scenarios and a method is presented for early screening of MCI in home settings. Nevertheless, cognition related gait impairments can be identified through comparative analysis of subject’s single and dual-task (with cognitive loading) i.e. dual-task cost performance. However, as gait is a complex motor activity and can be effected by other factors like visual problems, musculoskeletal issues etc. Therefore, one potential future work could be to perform comprehensive research on gait biomarkers comparison across multiple causes of gait deterioration. In addition, in future longitudinal study can be performed to map progressive deterioration of gait parameters to cognitive decline and evolution of dementia.

Another potential area is differential diagnosis i.e. to identify the underlying cause of MCI or diagnosis of MCI sub-types through gait analysis. Recently, Chen et. al. [33] compared the gait of Parkinson’s Disease PD-MCI and Non-PD-MCI subjects in single-task walking scenario and reported a classification model to assist doctor’s decision. Certainly, more work is needed in this domain in order to accurately classify and to compare the gait of MCI sub-types under dual-task walking scenario.

V. CONCLUSION

This research work is the first to investigate comprehensive gait analysis of MCI people using shank mounted inertial sensors and highlights the potential of early detection of MCI through gait bio-markers in home settings. The MCI subjects presented significantly higher temporal features while having lower cadence, gait speed, and maximum shank angle in comparison with the cognitively normal people. In dual-task walking conditions, the gait parameters are also significantly different (lower p-values) than normal or single-task walking scenario. Therefore, dual-task walking scenario is recommended for prescreening of MCI people using gait analysis.

Gait biomarkers yielded slightly better MCI detection accuracy than MMSE, which is the most commonly administered psychometric screening assessment of cognitive functioning. The proposed automated MCI screening method, by utilizing inertial sensor based selective gait biomarkers and machine learning techniques, provided meaningful classification accuracy (sens. = 83%, acc. = 70%) as single modality prescreening tool. Owing to MCI mild and multi-domain symptoms, a multimodal system like combination of
speech analysis with gait parameters, could achieve better accuracy in detection of MCI people.

REFERENCES

[1] C. Patterson, World Alzheimer Report 2018. London, U.K.: Alzheimer’s Disease International, 2018.

[2] S. Yang, J. M. S. Boretti, K. Wong-Lin, and G. Prasad, “M/EEG-based biomarkers to predict the MCI and Alzheimer’s disease: A review from the ML perspective,” IEEE Trans. Biomed. Eng., vol. 66, no. 10, pp. 2924–2935, Oct. 2019.

[3] M. R. Ahmed, Y. Zhang, Z. Feng, B. Lo, O. T. Inan, and H. Liao, “Neuroimaging and machine learning for dementia diagnosis: Recent advancements and future prospects,” IEEE Rev. Biomed. Eng., vol. 12, pp. 19–33, 2019.

[4] A. H. Simonsen, S. K. Herukka, and N. Andreasen, “Recommendations for CSF Aβ biomarkers in the diagnostic evaluation of dementia.” Alzheimer’s Dementia, vol. 13, no. 3, pp. 274–284, Mar. 2017.

[5] K. Blnenow, “A review of fluid biomarkers for Alzheimer’s disease: Moving from CSF to blood,” Neuroil. Therapy, vol. 6, no. 1, pp. 15–24, Jul. 2017.

[6] A. Alberdi, A. Aztiria, and A. Basarab, “On the early diagnosis of Alzheimer’s disease from multimodal signals,” Artif. Intell. Med., vol. 71, pp. 1–29, Jul. 2016.

[7] J. M. Hausdorff, G. Yoge, S. Springer, E. S. Simon, and N. Giladi, “Walking is more like catching than tapping: Gait in the elderly as a complex cognitive task,” Exp. Brain Res., vol. 164, no. 4, pp. 541–548, Apr. 2005.

[8] S. W. Muir, M. Speechley, J. Wells, M. Borrie, K. Gopaul, and M. Montero-Odasso, “Gait assessment in mild cognitive impairment and Alzheimer’s disease: The effect of dual-task challenges across the cognitive spectrum,” Gait Posture, vol. 35, no. 1, pp. 96–100, 2012.

[9] S. Chen, J. Lach, B. Lo, and G.-Z. Yang, “Toward pervasive gait analysis with wearable sensors: A systematic review,” IEEE J. Biomed. Health Inform., vol. 20, no. 6, pp. 1521–1537, Nov. 2016.

[10] K.-H. Wolf, M. Kohlmann, M. Marschollek, R. Haux, and M. Gietzelt, “Inertial accuracy in detection of MCI people. speech analysis with gait parameters, could achieve better accuracy in detection of MCI people.

AHSAN SHAHZAD (Member, IEEE) received the B.Sc. degree (Hons.) in electrical engineering from the University of Engineering and Technology (UET), Lahore, Pakistan, in 2009, and the M.Sc. and Ph.D. degrees in electrical and computer engineering from the Gwango Institute of Science and Technology (GIST), Gwangju, South Korea, in 2014 and 2019, respectively.

From 2012 to 2018, he was a Research Assistant with the Communication and Sensors Network Laboratory, GIST. Since 2019, he has been an Assistant Professor with the Department of Computer and Software Engineering, National University of Sciences and Technology (CEME-NUST), Pakistan. His research interests include healthcare informatics, e-health systems, biomedical signal processing and application design, gait analysis, and pattern recognition.
ARESH DADLANI (Senior Member, IEEE) received the B.Sc. and M.Sc. degrees in electrical and computer engineering from the University of Tehran, Tehran, Iran, in 2007 and 2010, respectively, and the Ph.D. degree from the School of Information and Communications, Gwangju Institute of Science and Technology (GIST), Gwangju, South Korea, in 2015. From 2008 to 2010, he was with the School of Computer Science, Institute for Studies in Theoretical Physics and Mathematics (IPM), Tehran, as a Research Assistant. From 2015 to 2017, he was with the Center for Integrated Access Systems, Gwangju, as a Postdoctoral Researcher. Since September 2017, he has been with the School of Engineering and Digital Sciences, Nazarbayev University, Nur-Sultan, Kazakhstan, where he is currently an Assistant Professor and the Director of the Complex Networks and Systems Group. His research interests include modeling and analysis of complex system dynamics, network science, and applications of optimization techniques and modern queuing theory in wired and wireless communication networks.

HYEONIL LEE (Student Member, IEEE) received the B.Sc. degree in electronics and computer engineering from Chonnam National University (CNU), Gwangju, South Korea, in 2019, and the M.Sc. degree from the School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology (GIST), Gwangju. Since 2021, he has been a Researcher with the Korea Automotive Technology Institute, Jeonnam, Yeonggwang, South Korea. His research interests include deep learning, autonomous flight vehicles, vehicle control unit logic development, and control engineering.

KISEON KIM (Life Senior Member, IEEE) received the B.Eng. and M.Eng. degrees in electronics engineering from Seoul National University, Seoul, South Korea, in 1978 and 1980, respectively, and the Ph.D. degree in electrical engineering systems from the University of Southern California, Los Angeles, CA, USA, in 1987. From 1988 to 1991, he was with Schlumberger, Houston, TX, USA. From 1991 to 1994, he was with the Superconducting Super Collider Laboratory, Waxahachie, TX, USA. In 1994, he joined the Gwangju Institute of Science and Technology, Gwangju, South Korea, where he is currently a Professor. His current research interests include wideband digital communications system design, sensor network design, analysis and implementation both at the physical and at the resource management layer, and biomedical application design. He is a member of the National Academy of Engineering of Korea, a fellow of the IET, and a Senior Editor of the IEEE SENSORS JOURNAL.

* * *

HYEONIL LEE (Student Member, IEEE) received the B.Sc. degree in electronics and computer engineering from Chonnam National University (CNU), Gwangju, South Korea, in 2019, and the M.Sc. degree from the School of Electrical Engineering and Computer Science, Gwangju Institute of Science and Technology (GIST), Gwangju. Since 2021, he has been a Researcher with the Korea Automotive Technology Institute, Jeonnam, Yeonggwang, South Korea. His research interests include deep learning, autonomous flight vehicles, vehicle control unit logic development, and control engineering.