Early Diagnosis of Mild Cognitive Impairment through Balance Biomarkers using Wearable Inertial Sensors

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Annex A

THESIS ACCEPTANCE CERTIFICATE

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Dedicated to my family, especially my father and mother.

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Abstract

As human life expectancy continues to rise, the senior population is expanding, leading to a notable surge in degenerative conditions such as dementia. Dementia arises from the gradual decline of cognitive capacities and spotting its early stages, particularly Mild Cognitive Impairment (MCI), presents a challenge due to its transitional nature, distinct from a complete cognitive breakdown. Therefore, there's a critical need to control the progression of this condition through timely detection and initial intervention. Recent research has underscored the significance of analyzing postural balance as valuable indicator for predicting dementia in the elderly. For this study, data was acquired using wearable inertial sensor, attached to lower back of participants, while standing in four different conditions in the subsequent order: (1) eyes-open EO, (2) eyes-close EC, (3) right-leg lift RL, and (4) left leg lift LL. The results indicated that significant balance biomarkers were found for detection of MCI patients wherein four features were found in EO condition, three features in EC, one feature in RL condition and six features in LL condition. Hence, static balance assessment based using wearable inertial sensors in home settings provides significant balance markers which can be utilized for early detection of Mild Cognitive Impairment. Static eyes-open and left leg lift balance assessment features are significantly different than eyes closed and right leg lift conditions.

Keywords: *Static, Balance, Accelerometer, Sensor, Dementia, Alzheimer's disease, MCI*

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CHAPTER 1: INTRODUCTION

Dementia is a progressive and debilitating neurological disorder that profoundly affects cognition, memory, and daily functioning. Its global prevalence is on the rise, particularly as the aging population grows. On a global scale, around 50 million individuals are affected by dementia, and this figure is anticipated to rise to 152 million by the year 2050 [1]. Alzheimer's disease is a gradual neurological condition primarily impacting memory function, cognition, and behavior, and it ranks as the most prevalent cause of dementia worldwide. It typically begins with subtle memory issues and worsens over time, significantly impairing daily activities. The disease is driven by complex factors, including the buildup of abnormal proteins like amyloid plaques and tau tangles, disrupting communication between brain cells and leading to cell death. While there is no cure, available treatments focus on symptom management and slowing progression. Early diagnosis and intervention are vital. Both patients and caregivers face immense challenges as the disease advances, from personality changes to emotional and financial strains [41]. Alzheimer’s disease (AD) is the most common type of dementia constituting 60-80% of the cases [2]; progression of AD is called AD continuum which includes 3 phases: preclinical AD, mild cognitive impairment (MCI), and dementia due to AD [42]. MCI stands as a neurological disorder that acts as an intermediary phase between the ordinary declines in cognitive function linked to aging and more pronounced impairments like dementia. Individuals with Mild Cognitive Impairment (MCI) observe significant alterations in their cognitive capacities that exceed what is typical for their age but do not fulfill the criteria for a dementia diagnosis. These changes can impact memory, language skills, reasoning capabilities, and other cognitive functions. The significance of studying MCI lies in its potential as a precursor to conditions like Alzheimer's disease. Timely screening and detection of MCI can decelerate the progression of cognitive deficits; certain individuals diagnosed with MCI experience a return to normal cognitive function or maintain stability through suitable management and treatment. Given that mild symptoms often go unnoticed as part of the natural aging process, MCI becomes a crucial signal for intervening in dementia prevention. "Cognitively normal" pertains to individuals who demonstrate regular or typical cognitive abilities, devoid of substantial impairments or irregularities. These individuals usually perform within the anticipated spectrum on cognitive evaluations and tests.

Balance, also referred to as postural balance, refers to the ability to maintain a stable and upright position while standing, sitting, or moving. This complex skill relies on the interaction of various factors, including sensory input from visual cues, the inner ear's vestibular function, and the body's proprioceptive feedback. It also involves precise motor control that coordinates muscle and joint actions. Scientific research has shown a strong link between cognitive function and motor performance. In cases of Mild Cognitive Impairment (MCI), individuals often exhibit challenges in balance, which can be attributed to deficits in cognitive abilities, particularly executive function. These deficits can hinder the ability to make proactive postural adjustments, leading to difficulties in planning and shifting positions during activities like standing. This is particularly relevant in neurodegenerative conditions for instance MCI.

The diagnosis of MCI necessitates thorough assessments conducted by proficient medical professionals, a process that can consume a considerable amount of time and incur substantial costs. However, advancements in technology have introduced practical alternatives. Wearable inertial sensors and force platforms have emerged as valuable tools for assessing and identifying issues with postural balance. Inertial sensors are often integrated into wearable devices, enabling real-time capture of movement and acceleration data. This data can be used to analyze posture and balance during dynamic movements. Conversely, force platforms gauge the forces exerted by a person's body while standing or performing specific tasks. These technologies provide researchers and healthcare practitioners with in-depth insights into an individual's postural balance. By detecting irregularities, tracking rehabilitation progress, and devising targeted interventions, these tools are instrumental in enhancing balance and mitigating fall risks among vulnerable populations.

1.1 Motivation

While minor shifts in postural sway, such as static balance, might not significantly disrupt daily activities, they could signify a trajectory toward more pronounced decline. Detecting MCI in its early stages can help mitigate the pace of cognitive deterioration. It's worth noting that some individuals with MCI either return to normal cognitive function or remain steady through effective intervention and care [1]. Mild symptoms often go unchecked since they are considered as normal aging process. Therefore, MCI is considered an important intervention indicator of dementia prevention. Use of Wearable Inertial sensors will help in measuring postural steadiness because quick motor assessments diagnostic tool that is feasible, easy to use, portable, and inexpensive [12]. It takes minimal time for balance assessments in everyday life without clinical intervention.

1.2 Problem Statement

Extensive research is being conducted to identify individuals with MCI and healthy controls. To propose assessment of static balance biomarkers using wearable inertial sensors for early screening of Mild Cognitive Impairment (MCI).

1.3 Goals of Research

The main objectives of this research are outlined below:

- The principal goals of this study involve extracting and assessing a diverse set of static balance indicators to identify important markers for detecting Mild Cognitive Impairment (MCI) in comparison to Cognitive Normal (CN) individuals. This will be achieved through the utilization of wearable inertial sensors.
- Additionally, the study aims to determine which conditions yield the most precise differentiation during static postural sway across four distinct scenarios.

1.4 Organization of Thesis

This research work is planned as follows:

Chapter 1 briefly describes the scope, motivation, and problem statement of this dissertation, along with the research objectives.

Chapter 2 provides the works review and the major related literature done in the field of static balance assessment and MCI diagnosis. Posture stability features cohort from literature in vast fields of falls risk in aging and neurodegenerative diseases. It also comprehends research contributions.

Chapter 3 consists of the experimental protocol in detail. Subjects demography of participants used in this study. Mainly, features selected for evaluating balance biomarkers for discriminating MCI patients from CNs are explained in detail.

Chapter 4 presents detailed discussions of methodology used in this paper. All the statistical analysis, performance metrics and details of machine learning models and feature selection methods are explained.

Chapter 5 presents experimental results along with relevant figures and tables. A detailed discussion in comprehending results and insights are given.

Chapter 6 serves as the conclusion of the paper and outlines future prospects and potential avenues for further research.

CHAPTER 2: LITERATURE REVIEW

There is substantial research going on in detecting MCI patients from cognitive normal people using static balance biomarkers through scoring tests and force platforms but not much has been done in this area using inertial sensors.

According to [14], Elevated postural sway has been documented in both mild cognitive impairment and dementia cases, underscoring the potential of standing balance as a valuable biomarker for mild cognitive disorders and the advancement of neurodegenerative conditions. A meta-analysis has highlighted noteworthy distinctions in static balance performance between MCI groups and the aging population under eyes-open conditions. This implies that these groups rely on visual cues to uphold their postural stability, and any imbalance-related impairment contributes to slower information processing.

In [43], researchers did one leg standing balance test on AD, MCI and normal cognitive using inertial sensors. They found significant differences in AD vs. normal but not in MCI. Another study [44], used force platforms to assess and found significant differences in MCI patients from healthy controls. They assessed quiet stance with open and closed eyes conditions.

A study [15] found the correlations between cognitive deficiencies and balance impairments were particularly conspicuous within the group affected by Alzheimer's disease (AD). It did not find any significant balance biomarker between controls and AD cohort. However, have only assessed eyes-open condition and checked very limited number of balance characteristics in their study i.e. jerk (combined, ML, AP), RMS (combined, ML, AP) and ellipsis. Two more studies [45] and [46] used force platforms to evaluate and had found significant differences mainly in velocity static balance biomarker in MCI patients from healthy controls by assessing quiet standing activity conducted under conditions of both eyes open and eyes closed.

A recent study [3], developed new balance stability indicator with AUC=0.806, using stabilometer. Wearable Inertial sensors are quick motor assessments diagnostic tool that is feasible, easy to use, portable, and inexpensive [12]. It takes minimal time for balance assessments in everyday life without clinical intervention.

2.1 Static Balance Features

We have evaluated substantial amount of features from literature in vast fields of falls risk in aging and neurodegenerative diseases and most common features are presented in Table 1.

Table 1: Features for Measuring Postural Sway

Sr.no	Domain	Features name	References
1	Time	Mean distance	[12], [13], [22], [23], [24], [25], [26], [30]
2	Time	Average absolute acceleration magnitude (AAM) variation	[12]
3	Time	Summed Axis Acceleration (SAA)	[12]
4	Time	Summed Magnitude Area (SMA)	[12]
5	Time	Path length/ total excursion	[13], [23], [25], [26], [29], [31]
6	Time	Mean sway velocity	[10], [13], [22], [24], [25], [26], [27], [29], [32]
7	Time	Range of acceleration	[12], [13], [23], [24], [26], [29]
8	Time	RMS acc/ RDIST	[10], [12], [13], [22], [23], [24], [25], [26], [27], [29], [32], [33], [34], [35], [36], [37], [38]
9	Time	RMS ang velocity	[10], [12], [13],
10	Time	95% confidence circle sway area	[13], [23], [29]
11	Time	95% confidence ellipse area	[10], [13], [23], [24], [25], [26], [35]
12	Time	Sway area	[10], [13], [22], [23], [24], [29], [32], [38], [39], [40]
13	Time	Jerk	[12], [13], [22], [24], [25], [26], [29], [32], [34], [36]
14	Frequency	Total spectral power	[12], [13], [23], [29]
15	Frequency	Centroidal frequency/Spectral centroid	[12], [24], [25], [26], [27]
16	Frequency	SEF/95% frequency (F95)	[10], [12], [22], [23], [25], [28]
17	Frequency	SEF ang. Vel.	[10], [12], [13], [28]
18	Frequency	Frequency median / F50	[10], [12], [13], [25]
19	Frequency	Frequency dispersion	[12], [13], [22], [24], [26], [27]
			Continued on next page

20	Frequency	Peak freq	[12]
21	Frequency	Entropy acceleration	[10], [12], [13]
22	Frequency	Entropy ang. vel	[10], [12], [13]

2.2 Research Gaps

It is necessary to extract and assess an extensive spectrum of static balance biomarkers to identify meaningful indicators for detecting Mild Cognitive Impairment (MCI) in comparison to cognitively normal (CN) individuals. This exploration involves the utilization of wearable inertial sensors during periods of quiet standing. Balance parameters that were found to be meaningful differentiators included anterior-posterior (AP) sway ($p < 0.01$) and medio-lateral (ML) sway position ($p = 0.04$) in the context of eyes-open conditions, but not in eyes-closed conditions. These parameters contribute to the early differentiation between individuals with Mild Cognitive Impairment (MCI) and those with normal cognitive function (CN) [14].

A recent study [3], developed new balance stability indicator with AUC=0.806 using stabilometer but not in this field using inertial sensors. Wearable inertial sensors represent a swift and practical diagnostic tool for motor assessments. They offer portability, affordability, and require minimal time for conducting balance evaluations in daily routines without the need for clinical involvement. Consequently, the search for effective balance markers that demonstrate favorable AUC scores becomes imperative.

2.3 Research Contributions

This study aims to extract and assess an extensive array of static balance biomarkers with the goal of identifying significant markers for the detection of Mild Cognitive Impairment (MCI) as opposed to individuals with normal cognitive function. In this research, wearable inertial sensors are employed as the preferred technological tool. The study examines alterations in static postural sway across four distinct conditions and endeavors to identify the condition that yields more favorable outcomes.

CHAPTER 3: EXPERIMENTAL PROTOCOL

This section contains information about subjects' demographics and data acquisition protocol from sensors during quiet standing experiment. Additionally, it contains information about extracted features.

3.1 Subjects

Between October 2016 and February 2018, a total of 60 participants were selected from the registry of the National Research Center for Dementia in Gwangju, South Korea, for inclusion in this study. Among these participants, 30 were categorized as cognitively normal (CN), while the remaining 30 were diagnosed with Mild Cognitive Impairment (MCI) based on assessments conducted by medical professionals at Chosun University Hospital and Chonnam National University Hospital in Gwangju, South Korea. All experimental protocols adhered to the study's approved plan by the Institutional Review Board of Gwangju Institute of Science and Technology (GIST), South Korea, and informed written consent was obtained from all participants or their legal guardians prior to the experiments.

Each participant underwent clinical interviews, imaging procedures, and neuropsychological evaluations. Brain structure was assessed through magnetic resonance imaging (MRI), while positron emission tomography (PET) scans were employed to detect Beta-amyloid (βA) plaques. Cognitive abilities were gauged using the Mini-Mental State Examination (MMSE), with MCI classification applying to subjects scoring above 1.5 standard deviations from the norm, as outlined in references [16] and [17]. The participant pool consisted predominantly of CN individuals, including those with and without βA deposits, along with MCI cases primarily attributed to Alzheimer's disease (AD), encompassing both positive-amyloid and a few negative-amyloid instances.

Participants exhibiting focal brain lesions, dementia unrelated to Alzheimer's disease, and any other significant medical, neurological, or mental conditions that could influence cognitive functions and balance were excluded from the study.

One-way analysis of variance (ANOVA) was utilized to scrutinize disparities in demographic and cognitive factors between the two groups. The demographic and neuropsychological outcomes for all participants, along with their corresponding p-values, are presented in Table 2. Data is reported as means and standard deviations (Mean ± Std.) for continuous variables, while categorical variables are summarized as total counts. No noteworthy differences in age, gender, height, weight, or education level were found between the two groups.

Table 2: Demographics of Mild Cognitive Impairment (MCI) and Cognitively Normal (CN) Subjects

	CN	MCI	p-value
Subjects	30	30	-
Age (yr)	74.77 ± 4.797	76.53± 3.45	0.10696
Height(cm)	160.35± 7.06	162.76± 8.72	0.24279
Weight (kg)	61.64 ±7.21	63.26±8.24	0.42204
Gender (M/F)	16/14	20/10	0.29985
Education (yr)	9.97±4.498	10.70±4.55	0.53263
MMSE	27.53±2.029	25.87±3.36	0.02357

3.2 Data Acquisition Protocol

The experimental protocol involved participants wearing a Shimmer 3 inertial sensor [18], which comprised a triaxial accelerometer and a triaxial gyroscope. This wearable sensor was positioned on the lower back of the subjects (L3-L5 vertebrae) using an adjustable belt and was supervised by an observer. The sensor's x-, y-, and z-axes corresponded to the medio-lateral (ML), vertical (V), and antero-posterior (AP) orientations of the participant, respectively. Participants were instructed to stand upright with their arms at their sides in four different conditions: eyes-open, eyes-closed, right leg lift, and left leg lift. Refer to Figure 1 for an illustrative representation of these conditions.

Before data collection, the sensor underwent pre-calibration following the procedure outlined in reference [19]. It was set to measure within a range of ±4g, and the sampling rate was set to 64 Hz. The sensor's data was transmitted via Bluetooth to a nearby laptop and synchronized in time using the ConsensysPRO software [20]. During signal processing, the data underwent filtration by employing an 8th-order zero-phase low-pass Butterworth filter with a cutoff frequency of 5Hz, applied using the "filtfilt" function in MATLAB.

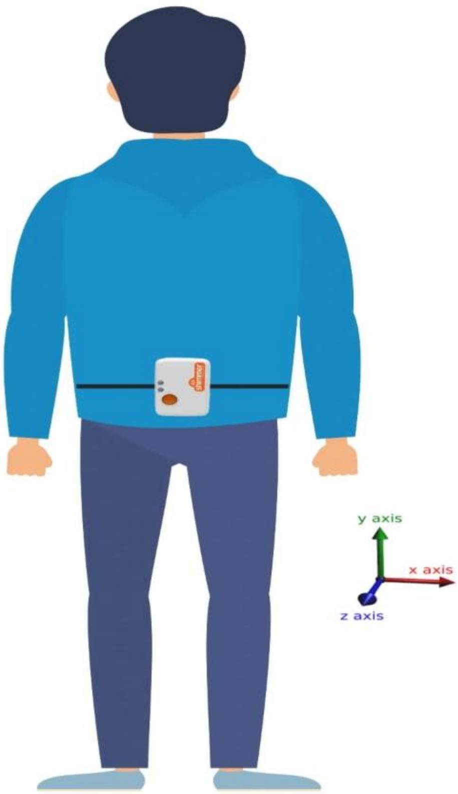

Figure 1: Orientation of Axes along Subject's Axis

The inertial sensor was composed of accelerometer and gyroscope. Acceleration data and angular velocity were extracted from it for our experiments for each condition. The visualization of acceleration data across data samples is provided in Figure 2. The Angular velocity signals across data samples visualization is presented in Figure 3. The amplitude of acceleration signal is low since it is providing information regarding static postural balance sway.

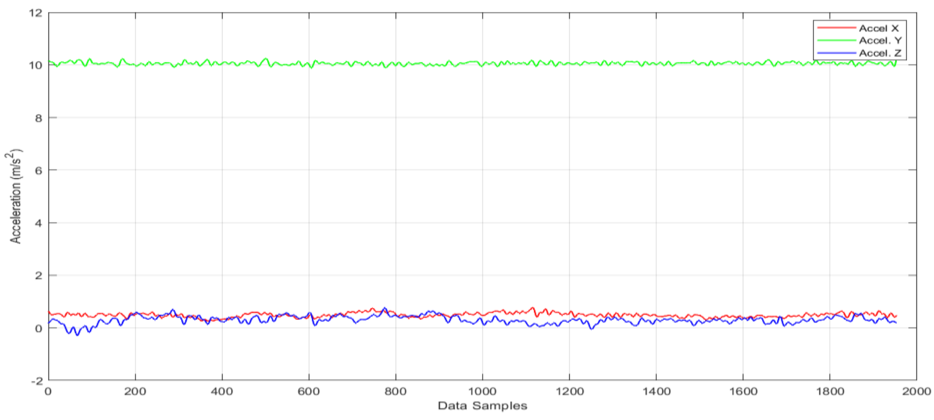

Figure 2: Acceleration Signal from Accelerometer along Data Samples

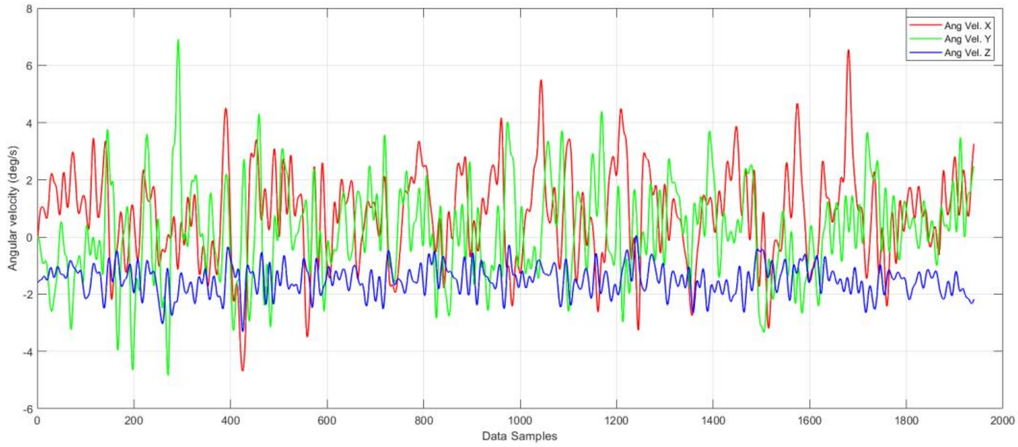

Figure 3: Angular Velocity Signals from Gyroscope along Data Samples

3.3 Feature Extraction

Some of the most common standard measures in the quantitative balance parameters in the time and frequency domains were calculated to measure postural balance in this study. These features are collected from vast domains assessing postural balance studies for static and gait balance in young and elderly people. These features gave valuable results for assessment of falls risk and diagnosis of neurodegenerative diseases such as Parkinson, dementia etc. using postural balance.

A total of 69 postural sway measures have been used; among these, 36 are time related features and 33 are frequency related features. Several parameters {6,..,8,37,..,57} are computed for all axis. Moreover, various parameters {1,..,4,10,..,17,22,..,33,58,..,69} are computed for each axis (ML, V and AP) and for SVM as well; few parameters {18,..,21,35,36} are calculated for some of these planes (AP-ML, ML-V, AP-V), and rest of the parameters {5,9,34} are calculated just for SVM. The magnitude of the acceleration signal vector is derived through (1).

$$SVM[n] = \sqrt{(A\_x[n]^2) + (A\_y[n]^2) + (A\_z[n]^2)} \quad (1)$$

A full list of features along with their units and directions are presented in Table 3 and 4. For each participant, all features were computed across the four distinct standing balance scenarios. A succinct explanation of these features is provided below, where N represents the quantity of time samples, and T signifies the chosen time interval for analysis.

3.3.1 Time Domain Features

In this section, a total of 36 time related features are explained along with definitions and formulas. These time domain features belong to distance, area and hybrid domain.

Mean Distance/Average Acceleration Magnitude (MDIST/AAM) {1,..,4} [10] [13] is the mean of the average acceleration magnitude. Average Absolute Acceleration Magnitude Variation (AAMV) {5} [12] is variation in average magnitude from mean. AAMV is calculated using (2).

$$AAMV = \frac{1}{N}\sum_{n=1}^{N-1}|SVM_{n+1} - SVM_n|. \quad (2)$$

Summed axis acceleration (SAA) {6,..,8} [12] is sum of all samples of individual acceleration signal and summed magnitude area (SMA) {9} [12] is sum of absolute of all acceleration signals. The path length (TOTEX) {10,..,13} [10], [13] is the total length of the acceleration path is estimated by summing the distances between consecutive points along the acceleration path. TOTEX for combined acceleration is calculated using (3) and for each axis by (4).

$$TOTEX = \sum_{N}^{N-1}\sqrt{(ML_{n+1} - ML_n)^2 + (V_{n+1} - V_n)^2 + (AP_{n+1} - AP_n)^2}. \quad (3)$$

$$TOTEX_{AP} = \sum_{n=1}^{N-1}|AP_{n+1} - AP_n|. \quad (4)$$

Where AP_n is the acceleration data at time sample n in each direction.

Mean Sway Velocity (MVELO) {14,..,17} [10], [13] is average velocity of acceleration path. The Range (R) {18,..,21} [13] and Jerk {22,..,25} [12] are computed as range of changes in amplitude and slope of acceleration, respectively. RMS {26,..,33} [10], [13] is root mean square of acceleration. RMS acceleration (RMS_A) and RMS Angular Velocity (RMS_G) for combine and for each acceleration signal is calculated using (5).

$$RMS = \sqrt{\frac{\sum A\,[n]^2}{N}}. \quad (5)$$

95% Confidence Circle Sway Area (AREA-CC) {34} [10], [13] is the area in circle which encloses all points in path of acceleration with confidence of 95%. AREA-CC is calculated using (6) by substituting (7) in it.

$$AREA-CC = \pi(MDIST + z_{0.5}s)^2. \qquad (6)$$

$$s = \sqrt{RMS^2 - MDIST^2}. \qquad (7)$$

Where $z_{0.5}$ value is 1.645.

Ellipse Area (AREA-CE) {35} [11] is the area in ellipses which encompasses all the points in ML-AP axis acceleration path with 95% confidence and is computed by the MATLAB implementation provided by [11]. Sway area (AREA-SW) {36} [10], [13] evaluates the area bounded by the acceleration path over time. AREA-SW is calculated using (8).

$$AREA-SW = \frac{1}{2T}\sum_{n=1}^{N-1} |AP_{n+1}ML_n - AP_nML_{n+1} \qquad (8)$$

Summary of time domain features along with names, units and directions are illustrated in Table 3.

Table 3: Summary of Time Domain Features

Features no.	Features name	Unit	Direction
1-4	Mean Distance/Average	m/s^2	SVM, ML,V and AP
5	Average Absolute	m/s^2	SVM
6-8	Summed Axis Acceleration	m/s^2	ML,V and AP
9	Summed Magnitude Area	m/s^2	SVM
10-13	Path Length (TOTEX)	m/s^2	SVM, ML,V and AP
14-17	Mean Sway Velocity	m/s	SVM, ML,V and AP
18-21	Range of Acceleration (R)	m/s^2	SVM, ML–AP, ML–V and AP–V
22-25	Jerk	m/s^3	SVM, ML,V and AP
26-29	RMS Acceleration (RDIST/	m/s^2	SVM, ML,V and AP
30-33	RMS Angular Velocity	deg/s	SVM, ML,V and AP
34	95% Confidence Circle	m^2/s^4	SVM
35	95% Confidence Ellipse	m^2/s^4	AP-ML
36	Sway Area (AREA-SW)	m^2/s^5	AP-ML

3.3.2 Frequency Domain Features

This section encompasses various frequency/spectral domain measures, which are commonly utilized to assess postural steadiness. These measures within the frequency domain characterize aspects such as the shape or area of the power spectral density.

Total power spectrum (TP) {37,..,39} [12] represents the cumulative power of the power spectrum, calculated using the "pspectrum" function in MATLAB, derived from the acceleration signal. Centroidal frequency or spectral centroid (CFREQ) {40,..,42} [12] serves as an indicator for the center of mass of a spectrum, denoting the frequency at which spectral mass is concentrated. The spectral edge frequencies (SEF_A and SEF_G) {43,..,48} [12] signify the frequency below which 95% of the power spectrum is encompassed. Similarly, median frequency (FMED) {49,..,51} [12] signifies the frequency below which 50% of the power spectrum resides.

Frequency dispersion (FREQD) {52,..,54} [12] is a dimensionless parameter that quantifies the variability in the content of the power spectrum. Peak frequency (PFREQ) {55,..,57} [12] corresponds to the frequency with the highest value and is computed across all axes. Another feature, Mean frequency (MFREQ) {58,..,61} [10], [13], can be envisioned as the frequency an acceleration signal would have traversed if it had traced the total sway around a circle with a radius equal to the mean distance. This measure is proportional to the ratio of mean velocity to the mean distance. The combined calculation of MFREQ is obtained through equation (9), while the per-axis calculation is achieved using equation (10).

$$MFREQ = \frac{MVELO}{2\pi MDSIT}. \tag{9}$$

$$MFREQ_{AP} = \frac{MVELO_{AP}}{4\sqrt{2}MDIST_{AP}}. \tag{10}$$

Lastly, Entropy Acceleration (ENT_A) and Entropy Angular Velocity (ENT_G) {65,..,69} [12] denote the power spectrum entropy of the acceleration and angular velocity signals, respectively.

These features are selected because they are easy to compute and give substantial information regarding postural steadiness. A summary of frequency domain features along with unit and directions are mentioned in Table 4.

Table 4: Summary of Frequency Domain Features

Features no.	Features name	Unit	Direction
37-39	Total Spectral Power (TP)	μ	ML,V and AP
40-42	Centroidal Frequency/Spectral Centroid (CFREQ)	Hz	ML,V and AP
43-45	SEF/95% Frequency/F95 (SEF_A)	Hz	ML,V and AP
46-48	SEF Ang. Vel. (SEF_G)	Hz	ML,V and AP
49-51	Frequency Median/F50 (FMED)	Hz	ML,V and AP
52-54	Frequency Dispersion (FREQD)	-	ML,V and AP
55-57	Peak Frequency (PFREQ)	Hz	ML,V and AP
58-61	Mean frequency (MFREQ)	Hz	SVM, ML,V and AP
62-65	Entropy Acceleration (ENT_A)	-	SVM, ML,V and AP
66-69	Entropy Angular Velocity (ENT_G)	-	SVM, ML,V and AP

CHAPTER 4: METHODOLOGY

For signal processing, the Butterworth filter finds utility. This filter is adept at conserving the amplitude of a signal within a specific frequency range, simultaneously suppressing undesired frequencies. The hallmark of Butterworth filters lies in their "order," which dictates the rate of decline in attenuation, and their "cutoff frequency," which denotes the juncture at which high-frequency elements are dampened, permitting lower-frequency components to pass through. This mechanism proves effective in eradicating noise and undesirable frequencies from signals while upholding the integrity of desired information in the passband.

In our context, we employed an 8th order low-pass Butterworth filter with zero-phase characteristics. The designation "8th order" signifies that it possesses a filter order of 8, resulting in a more pronounced attenuation of high-frequency noise and a steeper roll-off, in contrast to lower-order filters. The attribute "zero-phase" indicates that this filter introduces no phase alteration, ensuring that the phase of the filtered signal remains unaltered. Lastly, the label "low-pass" signifies that this filter grants passage to low-frequency components while diminishing the presence of high-frequency components.

This variety of filter finds commonplace application in domains like audio processing and the analysis of biomedical signals, where safeguarding phase consistency and excluding high-frequency disturbances hold paramount importance.

4.1 Statistical Analysis

Assessment of data normality was conducted using the Shapiro-Wilk test, alongside the examination of histograms and boxplots. Given that a majority of balance characteristics did not exhibit a normal distribution, the Mann-Whitney U test was employed to identify significant disparities in each biomarker between individuals with MCI and those with normal cognitive function (CN).

4.1.1 Shapiro-Wilk Test

The Shapiro-Wilk test is engaged to determine the degree of conformity of a dataset to the attributes of a normal distribution. This evaluation yields both a test statistic and a corresponding p-value, where a lower p-value signifies a departure from normal distribution characteristics. Researchers typically utilize a predetermined significance level, like 0.05, to make a determination regarding the null hypothesis, which posits that the data adheres to a normal distribution. In cases where the test generates a p-value below the selected significance threshold, it signifies a substantial departure of the data from normality.

4.1.2 Mann-Whitney U Test

The Mann-Whitney U test, is a statistical analysis which is non-parametric and it is applied to compare two distinct independent groups or samples. This test investigates whether there exists a notable distinction in the distributions of these two groups, all while sidestepping the requirement for a predetermined data distribution assumption. The examination aims to determine if one group consistently exhibits higher or lower values compared to the other, rendering it valuable for ordinal or continuous data when conventional parametric assumptions are not satisfied.

4.1.3 One-Way ANOVA

The One-Way ANOVA is a statistical examination employed to contrast the means of three or more groups, aiming to identify significant distinctions among them. Its purpose is to ascertain whether the variance in the data predominantly arises from disparities between groups or from chance fluctuations within each group. If the obtained p-value falls below a selected significance threshold, it indicates that at least one group possesses a distinct mean compared to the rest.

4.2 Performance Metrics

For assessing the scores of discrete balance characteristics, the receiver operating characteristics (ROC) curve and the corresponding area under the curve (AUC) were utilized, accompanied by 95% confidence intervals (95% CI) [21] were calculated. To evaluate classification models, accuracy, sensitivity and specificity is used. The details of all these performance metrics are provided in this section.

4.2.1 Accuracy

Accuracy, a metric in classification, assesses the ratio of accurate predictions made by a model compared to the entire set of predictions. It's computed as the fraction of correct predictions relative to the total predictions. Although a widely utilized measure, accuracy might not be suitable for imbalanced datasets.

4.2.2 Sensitivity

Sensitivity, alternatively referred to as the True Positive Rate or Recall, is a metric in binary classification that quantifies the ratio of true positives (TP) accurately identified by a model in relation to all genuine positives (TP + False Negatives, FN). It evaluates the model's effectiveness in accurately categorizing positive instances, a critical consideration in fields such as medical assessments or anomaly identification. Elevated sensitivity values signify superior competence in recognizing positive cases.

4.2.3 Specificity

Specificity, a measure within binary classification, gauges the fraction of true negatives (TN) that a model accurately detects from all real negatives (TN + False Positives, FP). It signifies the model's proficiency in accurately categorizing negative instances, particularly pertinent in domains like medical diagnoses. Elevated specificity values indicate enhanced capability in minimizing incorrect identifications of negative cases.

4.2.4 AUC

AUC, an acronym for Area under the Curve, functions as a metric utilized in binary classification to assess a model's ability to distinguish between positive and negative instances. It computes the area under the ROC (Receiver Operating Characteristic) curve, where higher values indicate enhanced classification performance (with a perfect model attaining an AUC of 1 and a random model yielding an AUC of 0.5).

4.2.5 95% Confidence Interval (lower and upper)

Within a 95% Confidence Interval (CI), a range of values is encompassed, providing a level of confidence that a population parameter, like a mean or proportion, resides within this interval. The lower limit marks the minimum extent of this range, whereas the upper limit represents its maximum extent. In a 95% CI, there is a strong 95% probability that the true parameter value falls between these two boundaries, established based on sample data and statistical techniques.

4.3. Cross validation technique

Leave one out cross validation technique is explained in this section.

4.3.1 Leave One Out Cross Validation

Leave-One-Out Cross-Validation (LOOCV) is a cross-validation strategy utilized to evaluate the effectiveness of a machine learning model. This technique requires training the model on all but a single data point within the dataset and consequently evaluating it on the excluded data point. This iterative process is conducted for each data point in the dataset. LOOCV furnishes a reliable gauge of the model's performance, particularly advantageous with limited datasets, although it may incur substantial computational costs when dealing with larger datasets.

4.4 Feature Selection Methods

Since data is not normally distributed, Two were used in this study are mutual information and Wilcoxon rank-sum test.

4.4.1 Mutual Information

Mutual information functions as a metric quantifying the statistical interrelation of two random variables, Mutual Information gauges the extent to which information about one variable can be inferred by observing the other. This concept finds extensive use in fields such as machine learning and information theory, facilitating the assessment of relationships among variables or characteristics. Enhanced mutual information values correspond to stronger dependencies between the variables.

4.4.2 Wilcoxon Rank-Sum Test

The test of Wilcoxon rank-sum is a statistical technique that operates independently of specific assumptions about data distribution. It focuses on assessing the level of significant variation between two distinct groups or samples. This non-parametric method is particularly advantageous in situations where data does not conform to the assumptions of parametric tests, offering a reliable avenue for comparing independent groups.

4.5 Machine Learning Models

The working and use of machine learning models used in this study are explained in this section.

4.5.1 Decision Tree

A decision tree, an essential algorithm in machine learning, serves purposes in both classification and regression tasks. This algorithm constructs a representation of decisions or predictions resembling a tree structure. In this structure, each internal node stands for a specific feature, each branch corresponds to an assessment rule, and every leaf node encapsulates an ultimate result. The popularity of decision trees stems from their capacity to be interpreted and their adaptability, rendering them well-liked for various applications including data analysis and predictive modeling.

4.5.2 Naive Bayes

Naive Bayes stands as a machine learning algorithm employing probabilities for task classification, grounded in Bayes' theorem. It operates under the presumption of feature independence when conditioned on the class label, a simplification that remains effective in generating results. This approach is notably fitting for assignments such as text categorization and identifying spam, mainly due to its efficiency and capacity to provide meaningful outcomes even with a restricted volume of training data.

4.5.3 KNN

In the realm of supervised machine learning, the K-Nearest Neighbors (KNN) model finds its application in classification and prediction tasks. This algorithm determines the classification or value assigned to a specific data point by evaluating the prevailing majority class or average value among its k nearest neighbors within the training dataset. While KNN's strength lies in its adaptability and straightforwardness, making it valuable across a range of applications, it necessitates a thoughtful choice of the parameter k and can be susceptible to fluctuations in the scales of features.

4.5.4 SVM

The Support Vector Machine (SVM) emerges as a powerful algorithm within supervised machine learning, adept at addressing classification and regression assignments. Central to its purpose is the identification of an optimal hyper plane that adeptly separates data points into distinct classes, all while maximizing the gap between them. SVM demonstrates notable effectiveness when confronted with high-dimensional datasets, and it also provides the flexibility to utilize diverse kernel functions for capturing complex relationships inherent in the data.

4.5.5 MKL-SVM

The Multi-Kernel Learning Support Vector Machine represents an enhanced iteration of the traditional SVM, designed to improve classification performance by amalgamating multiple kernels. Through the automated selection and weighting of diverse kernels, this approach excels at capturing a wide array of patterns present in data, particularly advantageous for complex problems characterized by varied data representations. The MKL-SVM holds relevance across diverse domains like image analysis, bioinformatics, and natural language processing, playing a pivotal role in enhancing both model accuracy and robustness.

CHAPTER 5 EXPERIMENTAL RESULTS

In this section, AUC results, classification results using significant features are presented in detail. Furthermore, classification outcomes were assessed utilizing feature selection techniques, namely Mutual Information and Wilcoxon rank-sum test, applied to the complete feature set is illustrated. Lastly, comparison of significant features with MMSE score of subjects are explained.

5.1 Mann-Whitney U Test Results

Since data is non normal, we used Mann-Whitney U test for significant feature analysis and got following results presented in Table 5 presents results of Mann-Whitney U test. Significant values of p is less than 0.05.

Table 5: Significant Features

Conditions	Sr.no	Features Name	p-values (p<0.05)
Eyes-Open	1	MDIST	0.0111
	2	RMS_A	0.0111
	3	AREA-CC	0.0177
	4	SEF_G V	0.0097
Eyes-Close	1	MDIST	0.0126
	2	RMS_A	0.0126
	3	AREA-CC	0.0177
Right Leg Lift	1	MDIST	0.0414
Left Leg Lift	1	MDIST	0.0462
	2	CFREQ AP	0.0319
	3	FREQD AP	0.0263
	4	ENT_A AP	0.0307
	5	ENT_G	0.0319
	6	MFREQ ML	0.0332
Mean of Conditions	1	MDIST	0.0163
	2	RMS_A	0.0234
	3	SEF_A ML	0.0111
	4	SEF_G V	0.0307
	5	CFREQ ML	0.0082
	6	FREQD ML	0.0132
	7	ENT_A ML	0.0137
	8	Jerk AP	0.0285
	9	MFREQ ML	0.0137

four features in eyes open condition, three features in eyes close condition, one feature in right leg lift condition, six features in left leg lift condition and nine features in mean condition generates significant results according to Mann-Whitney U test.

5.2 AUC Results

This study marks the initial investigation into disparities in standing balance attributes derived from accelerometers between individuals with normal cognitive function and those with Mild Cognitive Impairment (MCI). Mean of conditions is the mean value taken across all standing balance conditions (EO, EC, RL, and LL) of each feature per subject.

The key results suggest that balance characteristics exists across all assessed conditions which could demonstrate significant dissimilarities where value of $p<0.05$ between MCI and CNs. P-values and AUC with 95% confidence lower and upper intervals of significantly different features are illustrated in Table 6.

Within a 95% confidence interval, there is a strong assurance of 95% probability that the true parameter value is encompassed by the range defined by these two limits, which is established based on sample data and statistical techniques.

Table 6: Results of Significant Balance Biomarkers to Discriminate MCI and CN

Conditions	Sr.no	Features name	AUC	CI lower	CI upper
Eyes-Open	1	MDIST	**0.6899**	0.5319	0.8058
	2	RMS_A	**0.6899**	0.5319	0.8058
	3	AREA-CC	0.6572	0.5189	0.7956
	4	SEF_G V	**0.6922**	0.5584	0.826
Eyes-Close	1	MDIST	0.6678	0.5307	0.8049
	2	RMS_A	0.6672	0.5301	0.8044
	3	AREA-CC	0.6583	0.5201	0.7965
Right Leg Lift	1	MDIST	0.6411	0.501	0.7812
Left Leg Lift	1	MDIST	0.6333	0.4924	0.7742
	2	CFREQ AP	**0.6806**	0.5451	0.816
	3	FREQD AP	**0.6811**	0.5458	0.8165
	4	ENT_A AP	**0.6733**	0.537	0.8097
	5	ENT_G	0.66	0.522	0.798
	6	MFREQ ML	**0.6711**	0.5345	0.8078

Continued on next page

Mean of Conditions	1	MDIST	0.6589	0.5207	0.797
	2	RMS_A	0.6494	0.5102	0.7887
	3	SEF_A ML	**0.7156**	0.5853	0.8458
	4	SEF_G V	0.6472	0.5078	0.7867
	5	CFREQ ML	**0.7067**	0.575	0.8383
	6	FREQD ML	**0.7078**	0.5763	0.8392
	7	ENT_A ML	**0.6978**	0.5648	0.8308
	8	Jerk AP	**0.6794**	0.5439	0.815
	9	MFREQ ML	**0.7011**	0.5686	0.8336

5.3 Classification using Significant Features

We employed several fundamental machine learning models, including support vector machine (SVM), decision tree (DT), Naïve Bayes (NB), K-nearest neighbors (KNN), and MKL-SVM. These models were applied exclusively to the significant features identified within each condition, as well as the mean of conditions.

Figure 4 illustrates the methodology used for classification of models using significant features in each condition. Significant features calculated through Mann-Whitney U test in above section. Then data is split through 10 fold cross validation to maximize the training because data set is small. After that, testing of model is checked and results are produced.

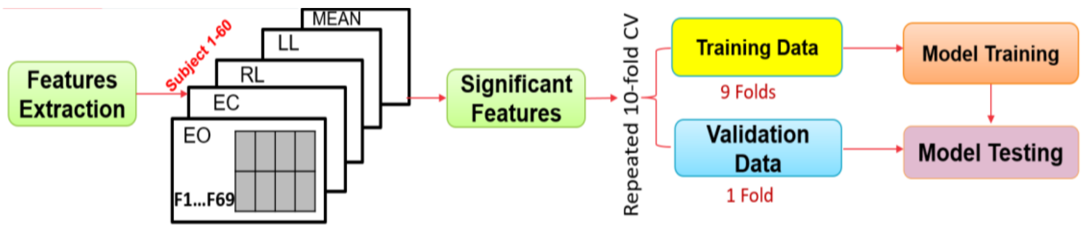

Figure 4: Methodology of Classification using Significant Features

The classification performance was measured through classification accuracy (Acc.), sensitivity (Sens.), and specificity (Spec.). The specific outcomes achieved by each classification model are outlined in Table 7. The SVM technique resulted in an accuracy of 70%, coupled with a sensitivity of 80%, under the eyes-open condition. Most significant features are present in mean of conditions. Therefore, it is better to take mean of all quiet standing stance and then do analysis. MKL-SVM is yielding 68.3333% accuracy in left leg lift condition. The other models are not providing good results with significant features. Advance machine learning models need to be applied.

Table 7: Performance Comparison of Various ML Models yielding Results using only Significant Features

Model	Conditions	Hyper parameter	Acc. (%)	Sens. (%)	Spec. (%)
SVM	**Eyes-Open**	**C=60**	**70**	**80**	**60**
	Eyes-Close	C=20	60	73.3333	46.6667
	Right Leg Lift	C=300	60	80	40
	Left Leg Lift	C=20	58.3333	60	56.6667
	Mean of Conditions	C=20	61.6667	70	53.3333
DT	**Eyes-Open**	Max_depth=2	65	93.3333	36.6667
	Eyes-Close	Max_depth=3	65	86.6667	43.3333
	Right Leg Lift	Max_depth=2	66.6667	93.3333	43.3333
	Left Leg Lift	Max_depth=2	60	76.6667	43.3333
	Mean of Conditions	Max_depth=3	66.6667	53.3333	80
NB	**Eyes-Open**	-	65	73.3333	56.6667
	Eyes-Close	-	63.3333	76.6667	50
	Right Leg Lift	-	56.6667	73.3333	40
	Left Leg Lift	-	65	60	70
	Mean of Conditions	-	63.3333	60	66.6667
KNN	**Eyes-Open**	K=3	56.6667	63.3333	50
	Eyes-Close	K=3	51.6667	60	43.3333
	Right Leg Lift	K=3	53.3333	56.6667	50
	Left Leg Lift	K=3	51.6667	46.6667	56.6667
	Mean of Conditions	K=3	63.3333	70	56.6667
MKL-	**Eyes-Open**	C=250	66.6667	76.6667	56.6667
	Eyes-Close	C=80	61.6667	73.3333	50
	Right Leg Lift	C=80	60	70	50
	Left Leg Lift	C=60	68.3333	86.6667	50
	Mean of Conditions	C=40	65	86.6667	43.3333

5.4 Classification using all Features

Figure 5 illustrates the methodology used for classification of models using significant features in each condition. Significant features calculated through Mann-Whitney U test in above section. Then 2 feature selection methods are applied namely, Mutual Information and Wilxocon Ranksum test. Both of these are wrapper methods. We did not apply SFFS feature selection methods because they may lead to over fitting and affect the results.

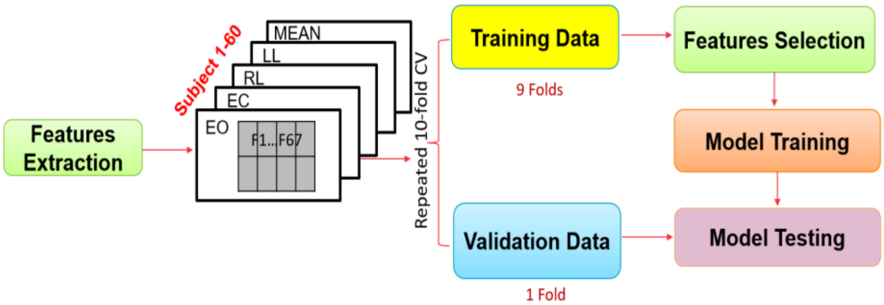

Figure 5: Classification Methodology using all Features with Feature Selection Methods

Results of multiple machine learning models along with best combination of features are presented in following tables. No of features is presented by nbf and it provides the information that best accuracy of models is achieved at specific combination of number of features.

Table 8: Performance Results of Decision Tree Model

	Max_depth	**nbf**	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	3	4	65	90	40	Mutual information
Eyes-Close	3,4,5	6	65	83.3333	46.6667	
Right Leg Lift	2	5	61.6667	83.3333	40	
Left Leg Lift	3	3	66.6667	73.3333	60	
Mean of Conditions	2	4	70	83.3333	56.6667	
	Max_depth	**nbf**	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	2,3	8	66.6667	70	63.3333	Wilcoxon
Eyes-Close	3	1,2,3	70	96.6667	43.3333	
Right Leg Lift	2,3	1,2,3	66.6667	93.3333	40	
Left Leg Lift	3,4	1	61.6667	80	43.3333	
Mean of Conditions	4	2,3	70	90	50	

In Table 8, results of decision tree model is illustrated with optimized max_depth hyper parameter. Decision tree is yielding 70% accuracy with high sensitivity in mean of conditions using Wilcoxon feature selection method.

Table 9: Performance Results of Naïve Bayes Model

	nbf	Acc. (%)	Sens. (%)	Spec. (%)	FSM
Eyes-Open	6	60	56.6667	63.3333	Mutual information
Eyes-Close	12	50	70	30	
Right Leg Lift	2	56.6667	30	83.3333	
Left Leg Lift	5	55	40	70	
Mean of Conditions	5	51.6667	40	63.3333	
	nbf	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	7	65	70	60	Wilcoxon
Eyes-Close	6	63.3333	73.3333	53.3333	
Right Leg Lift	1	56.6667	73.3333	40	
Left Leg Lift	1	65	80	50	
Mean of Conditions	2	61.6667	76.6667	46.6667	

In Table 9, results of naïve bayes model is illustrated with no hyper parameter. This model is yielding 65% accuracy with high sensitivity in left leg lift conditions using Wilcoxon feature selection method.

Table 10: Performance Results of KNN Model

	k	nbf	Acc. (%)	Sens. (%)	Spec. (%)	FSM
Eyes-Open	3	1	56.6667	63.3333	50	Mutual information
Eyes-Close	2	4	51.6667	23.3333	80	
Right Leg Lift	3	4	66.6667	63.3333	70	
Left Leg Lift	3	12	53.3333	40	66.6667	
Mean of Conditions	3	12	56.6667	56.6667	56.6667	
	k	**nbf**	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	3	8	63.3333	63.3333	63.3333	Wilcoxon
Eyes-Close	3	5	58.3333	63.3333	53.3333	
Right Leg Lift	3	2	55	56.6667	53.3333	
Left Leg Lift	3	5	60	66.6667	53.3333	
Mean of Conditions	3	8	70	80	60	

In Table 10, results of KNN model is illustrated with optimized k hyper parameter. This model is yielding 70% accuracy with high sensitivity in mean of conditions using Wilcoxon feature selection method.

In Table 11, results of SVM model is illustrated with optimized c hyper parameter which is cost maximizing accuracy. This model is yielding 75% accuracy with high sensitivity in eyes open conditions using Wilcoxon feature selection method.

Table 11: Performance Results of SVM Model

	c	nbf	Acc. (%)	Sens. (%)	Spec. (%)	FSM
Eyes-Open	20	5	68.3333	76.6667	60	Mutual information
Eyes-Close	20	5	51.6667	66.6667	36.6667	
Right Leg Lift	20	4	65	66.6667	63.3333	
Left Leg Lift	20	12	53.3333	70	36.6667	
Mean of Conditions	20	7	56.6667	60	53.3333	
	c	**nbf**	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	60	7	75	83.3333	66.6667	Wilcoxon
Eyes-Close	20	5	61.6667	80	43.3333	
Right Leg Lift	40	2	61.6667	83.3333	40	
Left Leg Lift	40	1	65	83.3333	46.6667	
Mean of Conditions	20	4	66.6667	70	63.3333	

In Table 12, an advancement of SVM model is applied to get better results but since we used a total of 9 kernels of Gaussian and polynomials, it has given us over fitted results. The same hyper parameter c is used in MKL-SVM model i.e. cost.

Table 12: Performance Results of MKL-SVM Model

	c	nbf	Acc. (%)	Sens. (%)	Spec. (%)	FSM
Eyes-Open	160	5	71.6667	86.6667	56.6667	Mutual information
Eyes-Close	60	3	56.6667	26.6667	86.6667	
Right Leg Lift	80	5	63.3333	63.3333	63.3333	
Left Leg Lift	500	3	56.6667	40	73.3333	
Mean of Conditions	60	4	61.6667	66.6667	56.6667	
	c	**nbf**	**Acc. (%)**	**Sens. (%)**	**Spec. (%)**	**FSM**
Eyes-Open	120	7	68.3333	80	56.6667	Wilcoxon
Eyes-Close	60	1	61.6667	70	53.3333	
Right Leg Lift	80	1	60	70	50	
Left Leg Lift	60	1	68.3333	86.6667	50	
Mean of Conditions	40	9	65	86.6667	43.3333	

SVM and MKL-SVM gives best results among all models with accuracy range upto 75 for underlying conditions. We suggest using Wilcoxon rank sum feature selection method as it yields better results with all machine learning models. The superiority of MKL-SVM over traditional SVM can be attributed to its capability to harness multiple kernels simultaneously. While SVM employs a single kernel function to transform data into a higher-dimensional space for linear separation, this approach may not effectively capture the intricate patterns present in real-world data, which tends to be complex and diverse.

MKL-SVM overcomes this limitation by amalgamating multiple kernels, each tailored to capture specific nuances of the data's complexity. This fusion of kernels empowers MKL-SVM to more accurately model intricate relationships within the data, resulting in enhanced classification accuracy.

Moreover, MKL-SVM's automated weighting and kernel selection mechanism adapts to the unique attributes of the data, enhancing its ability to discern between classes in a more refined manner. This adaptability contributes to superior generalization and improved performance across a broader spectrum of datasets.

To summarize, MKL-SVM's capacity to encapsulate diverse patterns through multiple kernels and its flexible nature make it a more robust and adept choice, surpassing the traditional SVM, especially in situations where the data's complexity and diversity significantly impact classification outcomes.

Overall, we analyzed that eyes-open, left leg lift and mean of conditions are giving better results because significant features are present in these conditions. Wilcoxon rank sum feature selection method is giving better results than mutual information. Since the nature of our data was not normal, it is evident to say that Wilcoxon will give good results because it is utilized for such type of data.

5.5 Comparison of the Features with MMSE

The score of MMSE is a prevalent mental and cognitive assessment measure. It is employed to assess diverse cognitive aspects like memory, attention, and language, aiming to understand an individual's cognitive capabilities and detect possible cognitive deficiencies. With a score range typically spanning from 0 to 30, greater scores correspond to stronger cognitive tasks. MMSE is frequently administered in clinical contexts to evaluate cognitive deterioration and is frequently referenced in studies involving cognitive disorders and neurodegenerative conditions.

On our dataset, MMSE achieved area score of AUC=0.6694 (95% CI: [0.5326-0.8063) with 95% confidence lower and upper intervals, respectively. According to our results, several parameters achieved greater AUC score than AUC score of MMSE. Details of comparison among different conditions is given below.

In eyes open condition, the parameters: MDIST AUC=0.6899 (95% CI: [0.5319-0.8058]), RMS_A AUC=0.6899 (95% CI: [0.5319-0.8058]) and SEF_G V AUC=0.6922 (95% CI: [0.5584-0.826]) could discriminate MCI and CNs more acceptable than MMSE AUC=0.6694 (95% CI: [0.5326-0.8063]).

Moreover, in Left-leg lift condition, the parameters: CFREQ AP AUC=0.6806 (95% CI: [0.5451-0.816]), FREQD AP AUC=0.6811 (95% CI: [0.5458-0.8165]), ENT_A AP AUC=0.6733 (95% CI: [0.537-0.8097]) in AP direction and MFREQ ML AUC=0.6711 (95% CI: [0.5345-0.8078]) in ML direction could discriminate MCI and CNs more acceptable than MMSE.

In mean of all scenarios, SEF_A ML AUC=0.7156 (95% CI: [0.5853-0.8458]), CFREQ ML AUC=0.7067 (95% CI: [0.575-0.8383]), FREQD ML AUC=0.7078 (95% CI: [0.5763-0.8392]), ENT_A ML AUC=0.6978 (95% CI: [0.5648-0.8308]), MFREQ ML AUC=0.7011 (95% CI: [0.5686-0.8336]) in ML direction and jerk AP AUC=0.6794 (95% CI: [0.5439-0.815]) in AP direction could discriminate MCI and CNs more acceptable than MMSE. By taking mean of all conditions, the ROC analysis demonstrated the best feature to discriminate MCI from CNs is SEF_A ML AUC=0.7156 (95% CI: [0.5853-0.8458]).

The area under the curve ROC for significant features along with MMSE are illustrated for eyes open condition, left leg lift condition and mean conditions in Figure 6,7 and 8.

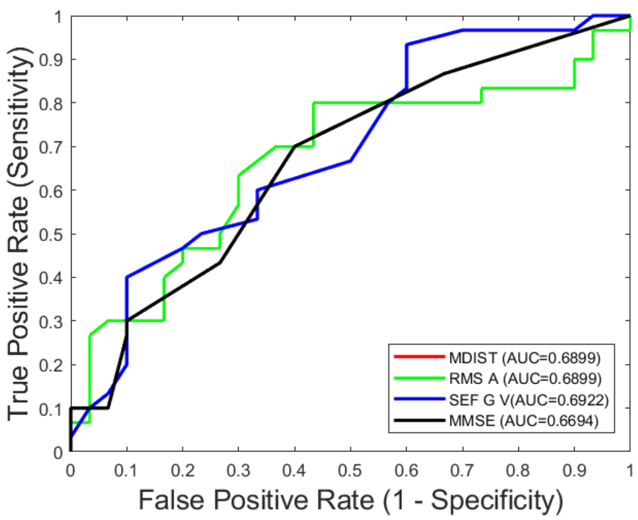

Figure 6: ROC Curve of Significant Features and MMSE along EO Condition

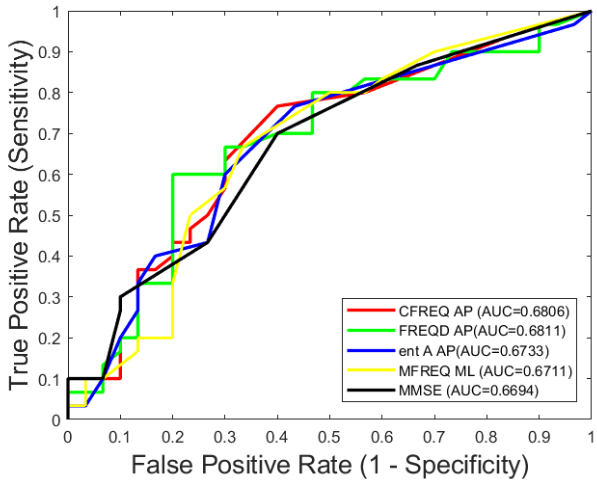

Figure 7: ROC Curve of Significant Features and MMSE along LL Condition

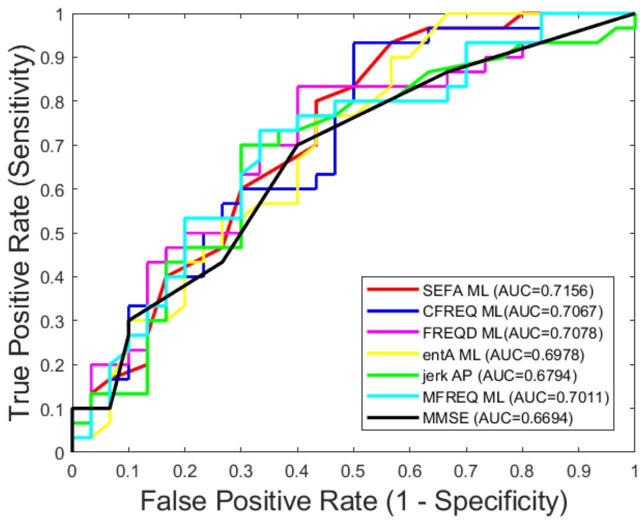

Figure 8: ROC Curve of Significant Features and MMSE along MEAN Condition

CHAPTER 6: CONCLUSION AND FUTURE WORK

Early identification of MCI patients is crucial to prevent or delay dementia progression. Our research endeavors to pioneer a comprehensive assessment of diverse balance biomarkers for the early detection of MCI patients compared to normal individuals. The scope of our study encompasses balance biomarkers that serve to identify impairments not only in MCI but those conditions associated with various cognitive disorders.

A total of 36 time related features and 33 frequency/spectral related features were extracted and evaluated in our study. This is the first study which evaluates such a wide range of balance and posture stability features. Our findings underscore the presence of significant biomarkers across all four conditions, with particular prominence observed in the eyes-open and left leg lift standing positions. Employing the mean of all conditions for each feature per subject yielded the highest count of significant biomarkers. Given the non-normal distribution of the majority of balance characteristics, test of Mann-Whitney U was engaged to pinpoint noteworthy distinctions in each biomarker's values between individuals with MCI diagnosis and those classified as healthy controls.

Notably, some static balance biomarkers exhibited superior AUC scores for MCI detection compared to the widely used MMSE whose full form is Mini-Mental State Examination. This underscores the potential of static balance assessment via wearable inertial sensors in supplying crucial biomarkers that facilitate the early recognition of MCI.

We observed noteworthy distinctions in static balance assessment features, particularly between eyes-open and left leg lift conditions in contrast to eyes closed and right leg lift conditions. Most prominent features in time domain are mean distance(MDIST), 95% confidence circle sway area(AREA_CC), jerk and RMS, whereas in frequency/spectral domain, SEF, mean (MFREQ), centroidal frequency(CFREQ), frequency dispersion (FREQD), and entropy (ENT) are significant balance biomarkers.

Importantly, our study pioneers the use of wearable sensor data to uncover balance biomarkers for diagnosing MCI patients and individuals without cognitive impairment. This approach offers robustness in gauging postural stability among MCI patients through prolonged, unsupervised monitoring, concurrently curbing the healthcare expenses linked to clinical assessments.

In forthcoming research, we intend to explore the optimal combination of measures from the complete feature set required for accurate MCI patient detection. Additionally, we plan to employ advanced machine learning models that effectively classify MCI and normal individuals using static balance metrics. We will further examine additional static balance biomarkers to enhance our understanding and diagnostic capabilities. Lastly, we will use data from total of 7 sensors: waist and both sides of thighs, shin, and toe. We will evaluate whether using all sensors generates better results and more number of significant biomarkers.

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