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A MACHINE LEARNING APPROACH TO CLASSIFY THE LEVEL OF COGNITIVE IMPAIRMENT AMONG ELDERLY POPULATION USING GAIT ANALYSIS

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***Abstract*— Cognitive impairment in the elderly population affects the performance of daily living activities which in turn, reflects the economic burden on society. Diagnosing cognitive impairment can be detained due to the medical assessment requiring considerable time and effort. This model uses a machine learning approach to classify the level of cognitive impairment using sequential gait analysis. The dataset consisting of gait sequence data collected from a group of 106 elderly participants in two sessions and the participants were categorized into three groups based on their scores on the mini-mental state examination. Each participant underwent the usual- and fast-paced walking along a straight line with two measurement units on each foot. These units are equipped with a 3-axis gyroscope and accelerometer. The sagittal angular velocity signals collected from each gait cycle using the measurement units were analyzed to construct gait parameters. A machine learning model called the long short-term memory network was employed to produce the classifiers that used the time-consecutive temporal gait parameters as predictors of cognitive impairment.**

This proposal helps to detect the CI in the elderly at the earliest stages without the clinical professional help, hence training them improve cognitive skills conveniently.

***Index Terms*—Cognitive Impairment, Long Short Term Memory Networks, Gait Sequence Analysis, Machine Learning, Temporal Gait Parameters.**

I. INTRODUCTION

COGNITIVE skills are also known as cognitive functions or cognitive abilities are brain-based skills which are needed in the acquisition of Knowledge, and reasoning. Cognitive impairment (CI) is defined as a decline in at least one of the following domains: memory, attention, orientation, judgment, language, problem-solving skills, perceptual speed, and executive function [1]. CI includes Mild Cognitive Impairment (MCI), Alzheimer's disease, Epilepsy-related cognitive dysfunction and various types of dementia. Mild Cognitive Impairment is the expected cognitive decline of normal ageing and a more serious decline of dementia. Severe cases of CI, such as dementia, result in a loss of capacity to speak, write, and comprehend the meaning or relevance of things, eventually making it unable to live independently [2]. People's cognitive capacity deteriorates considerably as they grow older. The global prevalence of CI is predicted to rise rapidly in the next years due to an extraordinary increase in life expectancy [7]. In order to combat CI, it's critical to have a diagnosis as soon as possible. Undiagnosed and untreated cognitive impairment in the elderly leads to a poor quality of life, a reduction in lifetime earnings, and an increase in deaths from fall-related injuries [8], malnutrition [9], muscle spasms [10], urinary tract infections [11], and pneumonia [12]. However, in practice, identifying CI is frequently missed or delayed since the vast majority of the elderly fail to disclose their condition in a timely manner, dismissing cognitive decline as a natural part of ageing. When there are atypical symptoms caused by multi-morbidity and poly pharmacy concerns, diagnosing CI might be difficult [13–15]. The use of traditional cognitive tests to detect the decline in cognitive processes adds to the difficulty of diagnosing CI in a timely manner. The examinations are lengthy, tedious, and time-consuming, and they necessitate the use of well-trained experts to ask questions, record responses, and assign scores, which is not ideal in a crowded clinical situation.

When compared to healthy controls, the elderly with dementia had a longer stride time [27], greater stride time variability [27], shorter step length [28–30], higher step length variability [30], and slower gait speed [27–30]. Despite the distinctive differences in gait characteristics between the cognitively healthy elderly and the elderly suffering from CI, only a few attempts to utilize gait characteristics in classifying the risk of CI have been made.

As a result, the goal of this model was to develop a new method for reliably classifying the risk of CI in the elderly based on gait features. Because the effects of cognitive dysfunction on gait characteristics during normal and fast-paced walking were distinct [24, 26], the investigation included both normal and fast-paced gait characteristics. In terms of classifiers, an advanced artificial neural network was used to discover patterns in the data, and traditional machine learning model-based classifiers were used to validate its classification performance.

The suggested method would pave the way toward defining the risk of CI that is less reliant on specialists and may be done in non-clinical situations, which would be beneficial.

II. COMPONENTS AND PROCEDURES

A. Hardware

(a)The hardware consists of 2 measurement units that consists of 3 axis accelerometer and gyroscope module MPU 6050. (b) Arduino with Bluetooth embedded module. These together form gait sequence measurement units which are a small device attached to the shoes. The Inertial Measurement Units (IMU) is used for recording the temporal gait parameter values by measuring the step, stance, swing and stride. (c) Android smart phone with at least 2 GB RAM and OS (version 5 or higher) is used to receive the gait sequence values through wireless connection (Bluetooth).

B. Software

Android Application was build using Android Studio IDE, the programming languages used was Java, XML for the UI and backend support from Cloud GPU. The classifier was established using machine learning algorithms and the dataset was tested and trained using jupyter IDE. The User Interface of the application consist of login and signup screen. The home screen consists of a simple button to start analysis, once the analysis is completed, the status consisting of the cognitive skills level is displayed to the user.

III. EXISTING SYSTEM

A. Mini-Mental State Examination

The Folstein test, often known as the Mini–Mental State Examination (MMSE), is a 30-point questionnaire used to assess cognitive impairment in clinical and research contexts. It is often used to test for dementia in medicine and allied health. It's also used to measure the level and development of cognitive impairment, as well as to track an individual's cognitive changes over time, making it a useful tool for documenting a patient's reaction to therapy. The MMSE was not designed to establish a diagnosis for any specific nosological entity on its own. The test takes around 5 to 10 minutes to administer and looks at capabilities including registration (repeating named prompts), attention and calculation, recollection, language, ability to follow basic directions, and orientation. It was first published in 1975 by Folstein et al. to distinguish organic from functional psychiatric patients, although it is extremely similar to, or even directly includes, tests that were in use before to its release. This is not a mental health evaluation. The current standard MMSE form, issued by Psychological Assessment Resources, is based on the original 1975 conception, with minor revisions by the authors. Advantages to the MMSE include requiring no specialized equipment or training for administration, and have both validity and reliability for the diagnosis and longitudinal assessment of Cognitive Impairment. It is effective for cognitive testing in the clinician's office or at the bedside because to its quick administration duration and ease of use. The MMSE has drawbacks in that it is influenced by demographic characteristics, with age and education having the biggest impact. The most common criticism of the MMSE is that it is insensitive to modest cognitive impairment and fails to properly distinguish people with mild Alzheimer's disease from normal persons. The MMSE has also been chastised for being insensitive to the gradual changes that occur in advanced Alzheimer's disease. The MMSE's content is heavily verbal, and there aren't enough items to appropriately assess visuospatial and/or constructional praxis.

IV. PROPOSED SYSTEM

Data is collected using measuring units attached to a pair of shoes by a classifier utilizing Long Short-Term Memory Networks. The model is based on a completely unbiased gait sequence. The technology delivers precise feedback as well as recommendations. The approach will be less expensive and time-consuming, with the added benefit of being neutral towards persons who are illiterate or blind.

V. FEASIBILITY STUDY AND IMPLEMENTATION STRATEGY

A. Feasibility Study

There is an increase in high-risk CI cases as regular assessments are being delayed or skipped due to the laborious and time-consuming procedures. The existing system, which is an MMSE examination, is biased toward the ill-educated and visually impaired patients. Ignoring a developing CI at the earlier stages affects the quality of life (both the patient and their family) and increases one's mortality due to falling related injuries, malnutrition and seizures. The existing system, which is an MMSE examination, is biased towards the ill-educated and visually impaired patients along with being time-consuming and comparatively costly. With the proposed system, the disadvantages can be eliminated by providing an unbiased result to each test case in a less time consuming and cost-effective manner.

B. Implementation Strategy

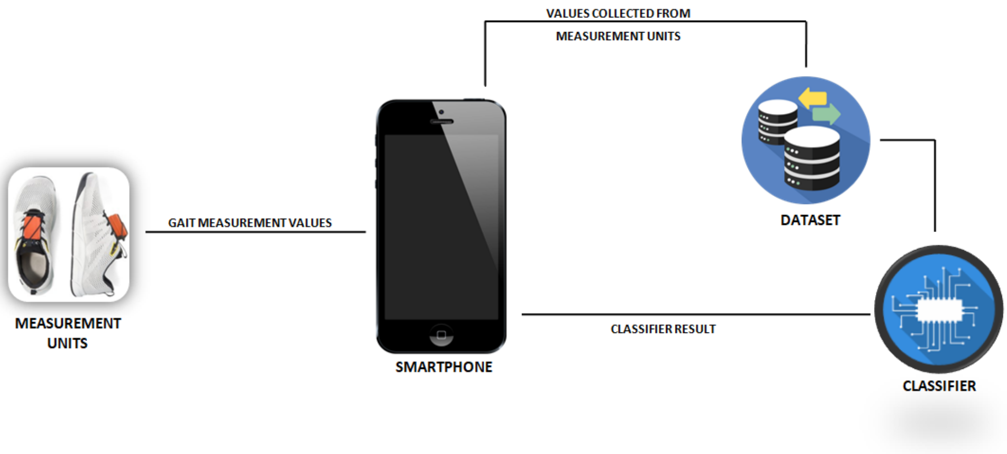

Fig 7. Data flow diagram

1. The Sagittal angular velocity signal is collected by analyzing the gait sequence using Inertial measurement units

2. The obtained data is transferred to a smartphone via Bluetooth

3. The raw data collected will be processed by an application running on the smartphone and will be send to a remote server for further classification

4. The requested service processes the given data using classifier called the Long Short-Term Memory Networks

5. The results will be sent back to the application, which presents the user with diagnosis result and suggestion

	Cognitively normal group	Low-risk CI group	High-risk CI group
Number of participants(female)	60(34)	36(24)	12(9)
Age(years)	76.40 ± 4.64	77.17 ± 6.65	77.42 ± 6.44
Education period (years)	8.47 ± 3.43	7.40 ± 4.47	6.50 ± 4.46
Weight (kg)	62.03 ± 9.38	58.90 ± 7.52	58.00 ± 4.88
Height (cm)	159.29 ± 6.78	154.65 ± 8.25	152.74 ± 8.47
MMSE score	26.34 ± 1.76	21.89 ± 1.12	16.75 ± 1.82

Fig 1. Inertial measurement units

VI. CLASSIFIER TRAINING AND EVALUATION

The pipeline for classifier training and evaluation is illustrated in Fig. 2.

A. Gait Parameters Extraction

By examining the y-axis angular velocity data obtained at each foot, which matched to the foot sagittal angular velocity signals, gait characteristics were extracted to produce the inputs for the classifiers. The sampling frequency for angular velocity data was 100 Hz. The angular velocity signals were band-pass filtered between 0.1 and 15 Hz before being normalized into the –1 to 1 range. The foot sagittal angular velocity signals were obtained simultaneously at the left foot (red solid line) and the right foot (blue solid line) in Fig. 3. (blue solid line). The periods of zero-crossing points, which correspond to the black hollow circles in Fig. 3, and high-amplitude peaks, which correspond to the black hollow rhombuses in Fig. 3, may be determined by identifying them in the foot sagittal angular velocity signals.

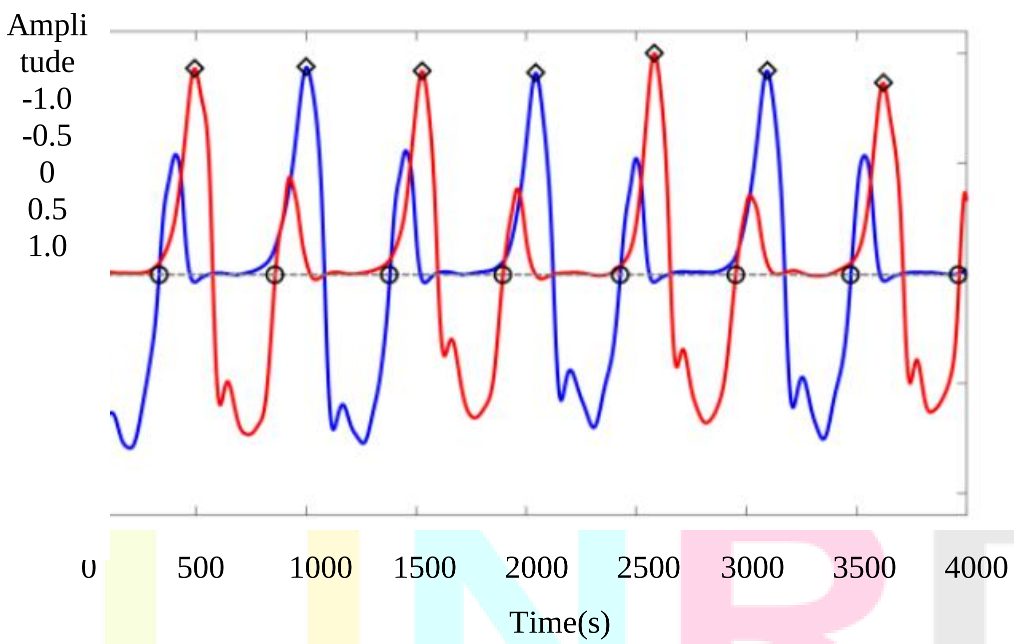

Fig 2. Gait graph

Extract the seven temporal gait parameters. Initial and terminal double-limb support phases are the first and the second period when both feet are simultaneously on the ground [35]. The initial double-limb support time was defined as the time between HS of the reference foot and TO of the contralateral foot, and the terminal double-limb support time was defined as the time between HS of the contralateral foot and TO of the reference foot. A phase when only the reference foot is in contact with the ground corresponds to a single-limb support phase [35]. The single-limb support time was defined as the time between TO of the contralateral foot and HS of the same foot. The stance time was defined as the time of phase initiated by HS of the reference foot and terminated by TO of the same foot, and the swing time was defined as the time of phase initiated by TO of the reference foot and terminated by HS of the same foot. The step time was defined as the time between HS of the reference foot and consecutive HS of the contralateral foot, and the stride time was defined as the time between HS of the reference foot and consecutive HS of the same foot. To scale the seven gait parameter sets into a uniform range, the minimum value of each gait parameter set for all trials of all participants at each speed condition was mapped to 0 and the maximum value of the same was mapped to 1.

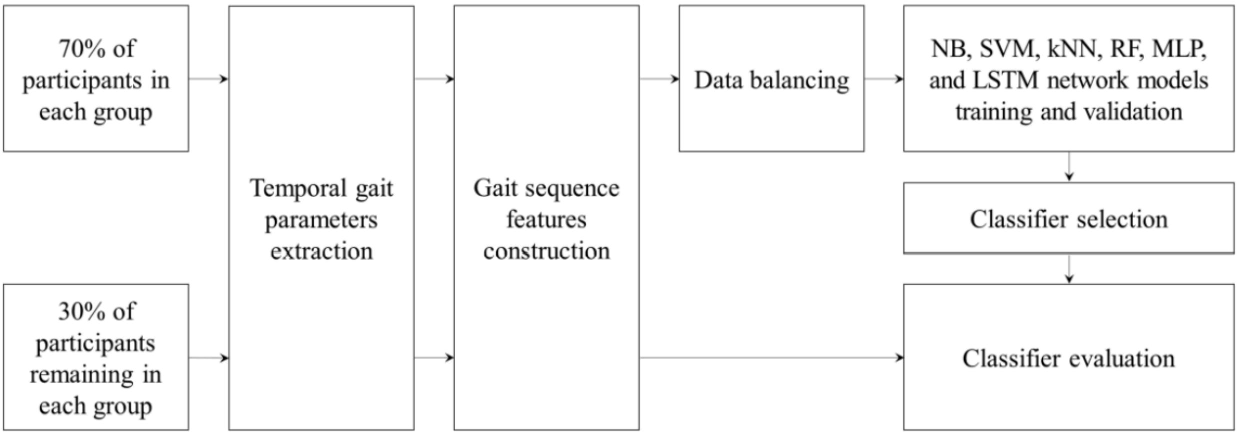

Fig 3. The pipeline of this model for training and evaluating the classifiers

VII. GAIT SEQUENCE FEATURES CONSTRUCTION

The seven temporal gait characteristics should be extracted. The first and second periods when both feet are on the ground at the same time are known as the initial and terminal double-limb support phases [35]. The time between HS of the reference foot and TO of the contralateral foot was defined as the start double-limb support time, and the time between HS of the contralateral foot and TO of the reference foot was defined as the terminal double-limb support time. A single-limb support phase occurs when just the reference foot is in touch with the ground [35]. The period between TO of the contralateral foot and HS of the same foot was designated as the single-limb support time. The phase begun time was specified as the stance time The swing time was defined as the time of phase began by TO of the reference foot and terminated by HS of the same foot, and it was defined as the time of phase initiated by TO of the reference foot and terminated by HS of the same foot. The step time was defined as the time between the reference foot's HS and the next HS of the contralateral foot, and the stride time was defined as the time between the reference foot's HS and the next HS of the same foot. The minimum value of each gait parameter set for all trials of all participants at each speed condition was mapped to 0 and the maximum value of the same was mapped to 1 to scale the seven gait parameter sets into a consistent range.

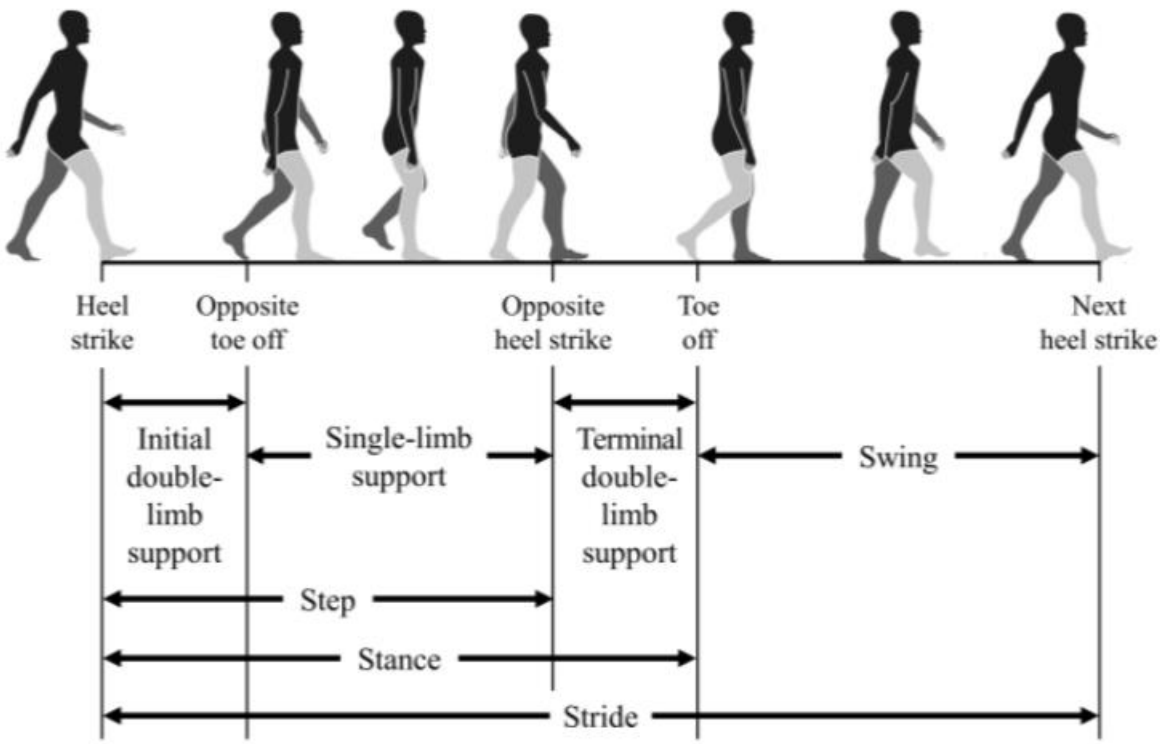

Fig 4. Gait phases in one gait cycle

Following that, gait sequence characteristics were constructed using time sequencing and sliding-window techniques. Fig. 5 demonstrates how the seven temporal gait factors were used to create gait sequence features. The sequence for first double-limb support time was made up of six initial double-limb support times, three from the left foot and three from the right, that were clustered in a window and were arranged chronologically. Shifting this window by two successive first double-limb support times, one from the left foot and one from the right foot, yielded the next sequence for initial double-limb support time.

The gait sequence characteristic for initial double-limb support time, which was labelled as IDS, matched to the sequences that comprised of initial double-limb support timings. Other gait sequence characteristics such as single-limb support time, terminal double-limb support time, stance time, swing time, step time, and stride time were computed in the same way and are reported in Table II as SLS, TDS, STN, SWN, STP, and STR. In addition to these seven gait sequence elements, 120 more gait sequence features were created by combining two or more of these seven gait sequence traits:

21 features are obtained by combining two of the seven features, 35 features are obtained by combining three of the seven features, 35 features are obtained by combining four of the seven features, 21 features are obtained by combining five of the seven features, seven features are obtained by combining six of the seven features, and one feature is obtained by combining all seven gait sequence features. The 127 gait sequence elements were designed for both normal and fast-paced walking. To study the effect of merging the gait characteristics at normal and fast-paced walking on categorizing the risk of CI, nine new features were generated by combining the

three best features at each speed condition. A total of 263 gait sequence characteristics were created and sent into the classifiers as input.

Abbreviation	Explanation
IDS	Gait sequence feature for initial double-limb support time
SLS	Gait sequence feature for single-limb support time
TDS	Gait sequence feature for terminal double-limb support time
STN	Gait sequence feature for stance time
SWN	Gait sequence feature for swing time
STP	Gait sequence feature for step time
STR	Gait sequence feature for stride time

Table 2. Gait sequence features

VIII. CONCLUSION

This model offered a unique strategy to classifying the risk of CI in the elderly by analyzing sequential gait features at normal and rapid walking speeds, as well as machine learning approaches. The LSTM network-based classifier performed exceptionally well in categorizing the elderly into cognitively normal, low-risk CI, and high-risk CI groups using gait sequence characteristics consisting of time-consecutive temporal gait metrics. This model might be one of the initial steps toward future studies that focus on a less professionalized evaluation of health risks in the elderly in non-experimental settings based on daily activities.

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