VISION ATTENTIVE MODEL FOR EARLY RECOGNITION OF SARCOPENIA WITH LIMITED MOBILITY OF ELDERS IN DOMESTIC ENVIRONMENT

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Master of Science (Major Component of Research)

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Thesis/Dissertation submitted in partial fulfillment of the requirements for the degree

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DECLARATION

I declare that this is my work, and this Dissertation does not incorporate without acknowledgment any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning. To the best of my knowledge and belief, it does not contain any material previously published or written by another person except where the acknowledgment is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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The above candidate has carried out research for the MSc by Research Dissertation under our supervision. We confirm that the declaration made above by the student is true and correct.

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DEDICATION

Dedicated

To my loving parents and wife

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ABSTRACT

Sarcopenia, a condition marked by age-related loss of muscle mass and function (especially in elders), is becoming more commonplace worldwide. Sarcopenia screening is necessary to identify at-risk people and implement measures to stop or slow their growth, especially in elders. Since many older people reject wearable sensor-based technologies, there is still a need for vision-attentive-based techniques for sarcopenia screening through the functional mobility of older people. In this research, combining the Timed Up and Go test (TUG-T), 3 Meters Walk Test (3mW-T), and fall score model built a vision attentive system for screening for sarcopenia in elders. The t-test applied to the collected dataset indicated a direct correlation between sarcopenia and factors such as TUG time ($p=0.004$), gait speed ($p=0.006$), fall score ($p=0.021$), and age ($p=0.002$). The primary discovery of this research indicates that older individuals afflicted by sarcopenia exhibit a TUG time exceeding 13.1 (±0.35) seconds, along with a gait speed slower than 0.7 (±0.07) m/s. Moreover, using the TUG test, gait speed, and fall score, the system successfully recognized sarcopenia in individuals with an accuracy of 93.7 (±1.9) %, 96.1 (±2.1) %, and 92.14 (±4.6) %, respectively. The method can potentially be an effective sarcopenia screening tool, as evidenced by its overall accuracy of 91.2%. These findings suggest that a vision-attentive system can be effective for sarcopenia screening and early detection, which may eventually enhance the elderly's clinical outcomes and quality of life.

Keywords: Geriatric assessment, Functional mobility estimation, Sarcopenia screening, TUG test, Vision attentive model

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LIST OF ABBREVIATIONS

Abbreviation	Description
3mWT	3-meters Walk Test
6mWT	6-Minute Walk Test
ADL	Activities of Daily Living
ANN	Artificial Neural Network
AWGS	Asian Working Group for Sarcopenia
BMI	Body Mass Index
DNN	Deep Neural Network
EWGSOP	European Working Group on Sarcopenia in Older People
FCE	Work-Specific Functional Capacity Evaluation
FMS	Functional Movement Screen
FRT	Functional Reach Test
GUI	Graphical User Interface
ICRP	International Commission on Radiological Protection
IDE	Integrated Development Environment
IMU	Inertial Measurement Units
ISAK	International Society for the Advancement of Kinanthropometry
NIOSH	National Institute for Occupational Safety and Health
ROC	Receiver Operating Characteristic
SDOC	Sarcopenia Definition and Outcomes Consortium
SFMA	Selective Functional Movement Assessment
SLST	Single Leg Squat Test
SPPB	Short Physical Performance Battery
TUG	Timed Up and Go
WHO	World Health Organization
YBT	Y-Balance Test

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CHAPTER 1

INTRODUCTION

1.1. Background

The World Health Organization (WHO) defines "*elderly*" or "*older person*" as someone who is 60 years of age or older [1-2]. This concept is predicated on the notion that most persons in their 60s and older are retired and have begun a time of reduced activity. The WHO also acknowledges that a person's chronological age may not accurately reflect their functional competence or capability to contribute to society [3]. Therefore, it is crucial to adopt a more comprehensive strategy that considers the diversity and complexity of aging and encourages healthy aging and well-being for everyone, regardless of age.

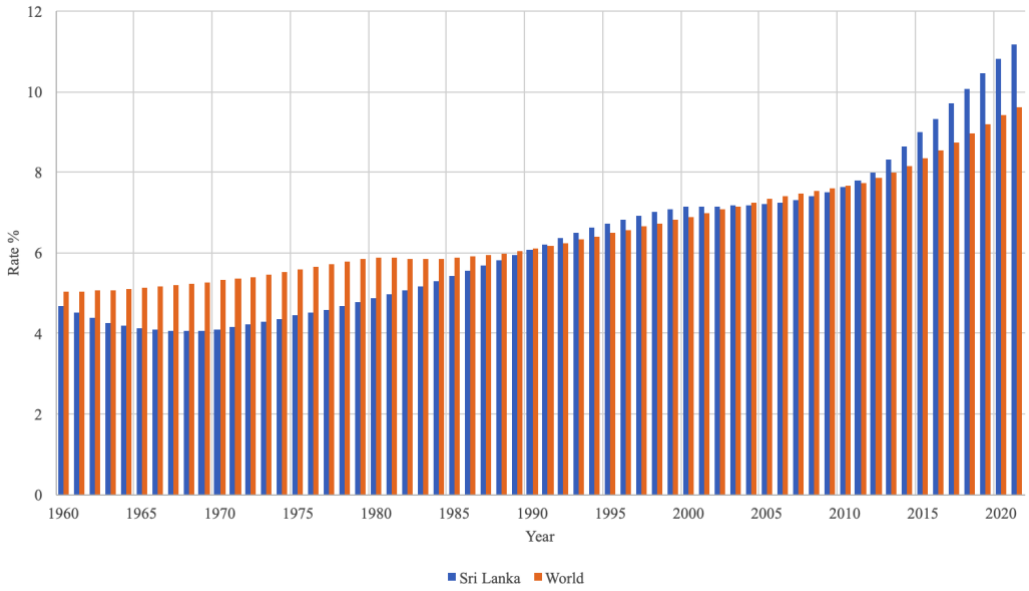


Fig. 1.1: Elder population growth from 1960 to 2021 (*source: United Nations Population Division. World Population Prospects: 2022 revision*)

Figure 1.1 depicts the rate of increase in elderly people in Sri Lanka and worldwide from 1960 to 2021. In Sri Lanka, the old population growth rate has been consistently rising over time, according to the data. The elderly population growth rate was 4.7% in 1960 and grew to 11.2% by 2021. Several causes, including longer life expectancies, lower fertility rates, and advancements in healthcare, can be blamed for the rise in the growth rate of the senior population. Sri Lanka has a comparatively slower pace of increase in its old population than the rest of the globe. Over time, the pace of growth in the senior population worldwide has also been rising. The growth rate of the old population was 5.1% in 1960 and grew to 9.6% by 2021. The over-60 population is expected to reach 20.1% (1 in 5 persons) in 2037 and 29.3% (almost 1/3 of the population) in 2050, according to predictions made by Gunarathna (2018) [4].

Along with the global expansion in the older population, the frequency of age-related health conditions has increased, posing considerable healthcare issues. The complex process of aging significantly alters the physiological makeup of the body, making it more prone to various diseases and health issues [5]. These age-related illnesses include a variety of chronic conditions, including diabetes, heart disease, and cancer, as well as degenerative diseases like sarcopenia, dementia, and frailty. Notably, the probability of developing a chronic illness is increasing, which is a significant cause for worry in an aging society since it raises morbidity and death rates, lowers quality of life, and increases healthcare costs. A comprehensive strategy that prioritizes proactive prevention, early identification, and efficient treatment methods for age-related chronic diseases is required to address these complex issues. The advent of physical and cognitive limits is one of the severe health issues aging brings. ***Sarcopenia***, which is characterized by a loss of muscle mass and strength, offers an extreme risk since it frequently causes fractures, falls, and other adverse health effects [6-7]. Frailty, which is characterized by weakness, tiredness, and decreased physical capability, poses a significant concern for older people and raises the risks of disability, hospitalization, and mortality. Additionally, a decline in physical or cognitive function, such as the onset of sarcopenia, dementia, and Alzheimer's disease, results in severe impairments in day-to-day functioning and increases the need for specialized care and support services.

Fostering comprehensive healthcare programs incorporating preventative measures, early intervention procedures, and effective management techniques is crucial in light of these difficulties. Age-related health issues can be considerably lessened by implementing personalized therapies, encouraging healthy lifestyle habits, and improving medical research and technology [8]. To ensure the health and quality of life of the aging population, it is crucial to invest in a robust healthcare infrastructure and promote multidisciplinary collaboration among healthcare professionals [9]. Society can successfully handle the complex and changing healthcare requirements of the elderly by emphasizing a comprehensive and proactive approach to elder care, encouraging a healthier and more robust aging process.

As the global population ages, the incidence of age-related health conditions continues to rise. Sarcopenia, a gradual loss of muscle mass, strength, and function, is one such condition that affects a significant proportion of older adults. Sarcopenia can lead to a range of adverse outcomes, including falls, disability, and decreased quality of life. Early detection and monitoring of sarcopenia are critical for preventing or delaying its progression and improving health outcomes in older adults.

Recently, there has been a growing interest in Sarcopenia condition. Sarcopenia is an aging-related loss of muscle mass and function [10]. It is common in older people, especially elders who live in long-term care facilities or hospitals [11]. Reduction of lean mass is a primary body composition change with aging. Low muscle strength is vital to senior physical disabilities and mortality [12]. Observing the loss of muscle mass with age is a simple approach to monitoring Sarcopenia. In clinical settings,

measuring hand-grip muscle strength (HGS) is a cost-effective and easy method to diagnose Sarcopenia [13].

The assessment of HGS helps plan and implement public health programs to preserve muscle strength in elderly people to enhance the health status of this population. Adequate protein intake is essential for muscle protein synthesis and the preservation or enhancement of muscle mass and strength. Protein synthesis, turnover, and breakdown decrease with age [14]. Therefore, protein requirement increases with aging [15]. Elders consume less protein-containing foods than other age groups. Inadequate protein intake can be attributed to muscle wasting, a frail immune status, and delayed wound healing. Insufficient protein intake leads to Sarcopenia, decreasing muscle strength [16-18].

Functional mobility tests provide a thorough examination of the effects of protein consumption and exercise on several physical function measures, such as gait speed, balance, and total functional ability, when they are incorporated into intervention programs. The effectiveness of protein consumption and exercise regimes in reducing sarcopenia may be precisely assessed by closely monitoring changes in functional mobility metrics, such as timed-up-and-go tests, chair stands, or the 6-minute walk test. In senior care, developing automated Sarcopenia techniques combining available mobility tests are crucial. The ability to diagnose sarcopenia early, a disorder marked by age-related muscle loss and diminished physical capability, is made possible by these technologies. These technologies automate the diagnostic process, facilitating prompt intervention techniques that enable medical providers to execute individualized treatment regimens and lifestyle changes at the first phases of muscle deterioration. This can improve older people's general quality of life and considerably delay the trend of muscle loss.

Moreover, using automated systems to incorporate standardized evaluation criteria maintain the assessment process's uniformity and impartiality. These techniques offer precise and trustworthy data for sarcopenia diagnosis and progression tracking by minimizing subjective biases and differences among assessors. In turn, this makes it possible for medical professionals to choose the best interventions and treatment methods for specific individuals.

1.2. Problem Statement

Sarcopenia has been linked to several detrimental health outcomes, such as falls, hospitalization, repeated injuries, functional decline, death, and other diseases. Among these negative impacts, falls, in particular, are a significant cause of mortality among older people. According to several studies, the risk of falling increases as sarcopenia progresses in elderly persons who have the condition. However, older people find it challenging to use wearable sensor-based activities, emphasizing the necessity for a vision-attentive-based development that may identify sarcopenia early in people with limited mobility.

Although sarcopenia has been associated with a higher risk of falling in multiple studies, there is still a need for research that concentrates on creating workable methods for the early detection of sarcopenia in elderly people with limited mobility. Although wearable sensor-based activities have been taken into consideration in specific research, it has been discovered that the elderly find them to be inconvenient. Therefore, additional research is required to develop visual, attentive-based solutions that may precisely identify sarcopenia in elderly people with restricted mobility and aid in avoiding falls and other adverse sarcopenia-related health effects.

1.3. Thesis Overview

The Overview of this thesis can be summarized as follows.

- **Chapter 1:** Provides an introduction to the thesis. It discusses the background that motivated this research and presents the problem statement addressed by this research work.

- **Chapter 2:** Presents a literature review on related concepts and past research work addressing similar problems. Moreover, related vision attentive methodologies for Timed Up and Go (TUG) time estimation, gait speed estimation, and fall prediction systems were explored.

- **Chapter 3:** This chapter focuses on creating and implementing an automated system that employs a vision-attentive technique to administer the TUG test and the 3-Meter Walk (3M-Walk) test. It explores the technological facets and techniques used to automate these functional mobility evaluations, offering insights into the conception and application of the vision attentive model for precise and effective test automation.

- **Chapter 4:** The detailed procedure of assessing and mapping muscle strength using a fall score is covered in Chapter 4. The algorithmic framework used to evaluate muscular strength and its relationship to fall scores is examined in this part, giving light to the usefulness of this strategy in foretelling and avoiding fall-related occurrences in sarcopenia.

- **Chapter 5:** The thesis provides a thorough Vision Attentive-Enabled Sarcopenia Screening Model in this chapter, incorporating the automated TUG and 3M-Walk tests as well as assessment of muscle strength. It explains the conception and use of this model, emphasizing its value in precisely defining and assessing sarcopenia and assisting in early identification and intervention options for those who are at risk.

- **Chapter 6:** In this part, the research's implications are critically examined. Any restrictions or difficulties observed during the study are also addressed, and prospective directions for further investigation and the use of the suggested

approaches are suggested. It highlights the importance of the automated method for estimating muscle strength and functional mobility tests for the early diagnosis and treatment of sarcopenia. It also discusses the research's enormous ramifications and recommends possible research and application opportunities in senior care and preventive healthcare.

CHAPTER 2

LITERATURE REVIEW

2.1. Mechanism, Categories, and Stages of Sarcopenia

The neuromuscular system's integrity, the amount of muscle fat, protein synthesis, and proteolysis are a few of the variables that can influence the development and course of sarcopenia. People with sarcopenia may be affected by multiple processes, and the relative importance of these mechanisms may change over time. Designing intervention studies that focus on one or more underlying mechanisms should be made more accessible by understanding these mechanisms and the underlying reasons behind them [19]. Figure 2.1 illustrates the process of sarcopenia occurring in individuals.

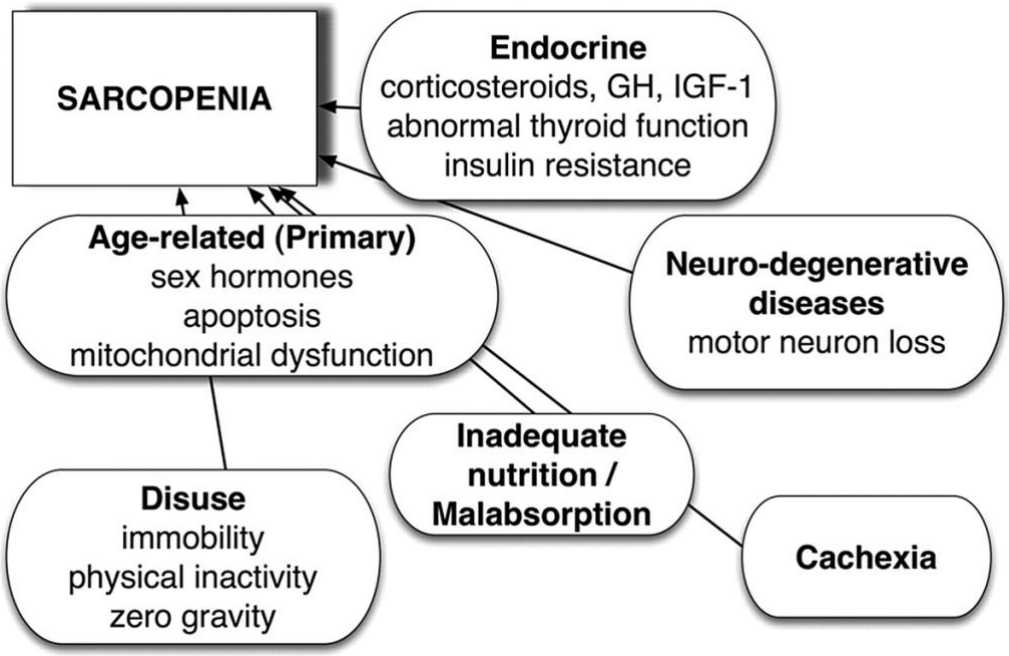


Fig. 2.1: Mechanism of sarcopenia. Adopted from [19]

Sarcopenia, a condition characterized by the progressive loss of muscle mass and strength, shares a multifaceted nature with dementia and osteoporosis. The origins of sarcopenia are diverse, stemming from factors such as aging, sedentary lifestyle, hormonal changes, and inadequate nutrition. It can appear in younger people, even though it is typically seen in older adults. Diverting primary from secondary sarcopenia can be helpful in clinical situations. If ageing is the only known cause, the condition is diagnosed as primary sarcopenia, also called age-related sarcopenia. Primary sarcopenia, on the other hand, is identified when it develops with the help of one or more other causes. The types and corresponding causes of sarcopenia are listed in Table 2.1.

TABLE 2.1: SARCOPENIA CATEGORIES AND IT'S CAUSES

Sarcopenia Category	Causes
Primary sarcopenia	-
Age-related sarcopenia	Only due to the aging.
Secondary sarcopenia	-
Activity-related sarcopenia	It can be caused by prolonged bed rest, a sedentary lifestyle, deconditioning, or zero-gravity circumstances.
Disease-related sarcopenia	It is associated with organ failure (brain, heart, kidney, etc.), an inflammatory condition, cancer, or an endocrine disorder.
Nutrition-related sarcopenia	results from a diet that is deficient in protein energy, as in cases of malabsorption, gastrointestinal problems, or the use of drugs that promote anorexia.

The stages of sarcopenia were outlined by the European Working Group on Sarcopenia in Older People (EWGSOP). Table 2.2 illustrates EWGSOP's proposed conceptual classification, which includes stages labeled as 'pre-sarcopenia,' 'sarcopenia,' and 'severe sarcopenia'.

TABLE 2.2: STAGES OF SARCOPENIA SYNDROME, ACCORDING TO THE EWGSOP

Stage	Muscle Mass	Muscle Strength	Performance
Pre-sarcopenia	↓		
Sarcopenia	↓	↓	
Severe sarcopenia	↓	↓	↓

In the initial phase known as "pre-sarcopenia," there is a discernible decline in muscle mass, yet it is accompanied by an absence of apparent effects on muscular strength or overall physical performance. Accurate methods that specifically measure muscle mass within typical populations are necessary to identify individuals in this stage.

2.2. Functional Mobility and Functional Capacity Assessments

Functional mobility screening procedures are evaluations or tests created to examine a person's capacity to perform functional movements and activities required for everyday life and physical performance. These exams assist in locating any movement restrictions, imbalances, or impairments that can raise the risk of injury or impair general physical performance. They are frequently employed in several contexts,

including physical rehabilitation, ergonomic workplace training, and sports and fitness. Table 2.3 shows the commonly used functional mobility screening procedures.

TABLE 2.3: FUNCTIONAL MOBILITY EVALUATION METHODOLOGIES

Method	Description
Functional Movement Screen (FMS)	One of the most popular approaches for functional mobility screening is FMS. A person's mobility and stability are evaluated using seven fundamental movement patterns. These exercises include the deep squat, the hurdle step, the inline lunge, the shoulder mobility, the active straight leg raise, the push-up, the trunk stability, and the rotary stability. To discover asymmetries or dysfunctions that require attention, each movement is graded on a scale from 0 to 3.
Selective Functional Movement Assessment (SFMA)	Determine the source of discomfort or functional limitations in patients by evaluating certain motions. When motions are broken down into different patterns, the SFMA determines if the issue is one of mobility or stability/motor control.
Y-Balance Test (YBT)	In situations related to sports medicine and rehabilitation, this screening technique is frequently employed. By testing how far a person can reach while standing on one leg, it evaluates their functional mobility and dynamic balance. Anterior, posteromedial, and posterolateral are the three directions. The Y-Balance Test aids in detecting asymmetries and functions as a risk indicator for injuries.
Functional Reach Test (FRT)	This exam is designed to evaluate functional mobility and static balance, particularly in senior populations. It gauges how far a person may advance while having a solid basis of support. The exam can help pinpoint balance problems and fall risk.

Single Leg Squat Test (SLST)	The SLST evaluates a person's strength, stability, and control of their lower extremities during a single-leg squat action. It is frequently used in sports performance training to find imbalances and weak points that might result in injury.
Timed Up and Go (TUG) Test	The TUG test is primarily used in geriatric and therapeutic settings to evaluate dynamic balance and functional mobility. It calculates how long someone can get out of a chair, walk a short distance, turn around, and return to a seat. The exam aids in identifying fall risk and mobility problems.

Methods for assessing a person's functional capacity are used to determine how well they can physically accomplish tasks and activities that are necessary for them to live their everyday lives, meet the demands of their jobs, or achieve specific functional objectives. These evaluations aid in figuring out a person's total useful capability, seeing any potential obstacles, and creating the best treatments or modifications. Table 2.4 depicts the most common functional capacity evaluation techniques.

TABLE 2.4: FUNCTIONAL CAPACITY EVALUATION METHODOLOGIES

Method	Description
Physical Performance Tests	Strength, endurance, flexibility, and balance are just a few of the physical traits evaluated in these tests. Grip Strength Test: Measures hand and forearm strength using a dynamometer. Sit-to-Stand Test: Assesses lower body strength and functional mobility by counting how many times a person can stand up from a chair and sit back down in a specified time. Timed Up and Go (TUG) Test: Evaluates functional mobility and balance by timing how long it takes a person to rise from a chair, walk a short distance, turn around, walk back, and sit down again.

	6-Minute Walk Test (6MWT): Measures the distance a person can walk in 6 minutes, assessing overall functional endurance.
Work-Specific Functional Capacity Evaluation (FCE)	FCEs are specialized tests created to measure a person's capacity to handle the physical demands of particular professional responsibilities. They are frequently used to assess a worker's competence to return to work safely following an illness or accident in occupational rehabilitation settings.
Aerobic Capacity Testing	These examinations concentrate on determining a person's level of cardiovascular fitness and stamina, frequently through activities like treadmill tests and cycle ergometer examinations. They can offer valuable data for formulating suitable exercise plans or determining a person's capacity for prolonged effort in activities.
Activities of Daily Living (ADL) Assessments:	These evaluations focus on a person's ability to perform basic self-care tasks required for daily living, such as dressing, bathing, grooming, and feeding.
Instrumented Gait Analysis	It involves evaluating a person's gait mechanics and walking patterns using specialist equipment. To pinpoint gait problems and assess the efficacy of therapies, it is frequently used in orthopedics and rehabilitation.

2.3. Vision Attentive Methodologies for Elderly Healthcare

An increasing number of people have been interested in using vision-attentive models to track their health in recent years [20]. These models examine photographs and videos of people to spot potential health problems using cutting-edge computer vision algorithms and artificial intelligence approaches. By providing non-invasive, real-time monitoring of various medical problems, from chronic illnesses to acute injuries, this technology has the potential to revolutionize healthcare [21-22].

The potential of vision-attentive models to identify health problems early-often before symptoms emerge-is one of its main advantages. Through immediate intervention and treatment, this early diagnosis may improve health outcomes and perhaps save lives.

A neurological disorder like Parkinson's disease or a stroke, for instance, may be indicated by changes in facial expression or movement patterns that may be picked up by visually attentive models [23]. The fact that they are non-invasive is another benefit of vision-attentive models. Vision-attentive models can monitor health without invasive procedures or painful instruments, in contrast to conventional health monitoring approaches. This can improve cooperation on the part of the patient and lower the danger of problems or infections brought on by intrusive treatments.

Using vision-attentive models, people may receive real-time feedback on their health state from the comfort of their own homes and enable remote health monitoring. People with chronic diseases or mobility challenges, who might find it challenging or inconvenient to get to a healthcare institution for monitoring, may find this very helpful [24].

Despite these advantages, using vision-attentive models for health monitoring has certain drawbacks as well. The requirement for high-quality photos and videos for analysis is one of the significant difficulties. Poor illumination, low-resolution cameras, or obstructed viewpoints might impact the accuracy and dependability of the models. Due to the possibility that the photographs and videos utilized for analysis include sensitive personal data, there are additional privacy and security considerations. Researchers are working on more sophisticated computer vision algorithms and artificial intelligence strategies to solve these problems and increase the precision and dependability of vision-attentive models. They are also looking for ways to improve security and privacy, such as adopting encryption or anonymization to safeguard personal data.

2.4. Functional Mobility Assessments for Sarcopenia

2.4.1. Sarcopenia Screening Through Timed-Up-and Go (TUG) Test

The TUG test is a simple and quick test that measures the time taken by an individual to stand up from a chair, walk a short distance (usually 3 meters or 10 feet), turn around, walk back to the chair, and sit down again. The test evaluates a person's balance, mobility, and overall functional capacity.

The TUG test is used to evaluate mobility and fall risk in older persons and screen for sarcopenia. A longer time needed to complete the TUG test, however, may indicate reduced muscle function and may call for additional testing for sarcopenia in the context of sarcopenia screening.

Martinez et al. [25] conducted an evaluation of the Timed Up and Go (TUG) test to determine its effectiveness in predicting sarcopenia among elderly patients admitted to hospitals. In elderly people, the TUG test is a good indicator of sarcopenia, according to their research. A sensitivity of 67% and a specificity of 88.7% were found for durations that were equal to or greater than the cut-off of 10.85 seconds.

To minimize the subjectivity of outcome measurements and to deliver additional data regarding patient performance, Dubois et al. [26] have employed the Microsoft Kinect ambient sensor to automate the TUG test. They used the depth images from the Kinect to identify each phase of the TUG test automatically.

For the diagnosis of sarcopenia, EWGSOP recommends using both low muscle mass and low muscle function (strength or performance). This was presented by Cruz-Jentoft et al. [27]. Sarcopenia refers to the age-related reduction in muscle mass, strength, and athletic performance. Due to its laborious diagnostic method, sarcopenia is seldom identified in clinical settings. Phu et al. [28] investigated the diagnostic use of the Short Physical Performance Battery (SPPB) for muscular illness sarcopenia. The SPPB stands as a concise, easily administered evaluation, offering an objective measure of both muscle strength and physical performance—integral facets of the underlying condition. 294 seniors (>65 years old) who live in the neighborhood were the subject of a cross-sectional investigation. Employing sanctioned methodologies, various essential metrics were meticulously gauged, encompassing appendicular lean body mass (ALM/h2), handgrip strength, sit-to-stand capacity, and an array of physical performance indicators, including gait speed, Timed Up and Go (TUG) time, and SPPB scores.

Kim and Won [29] introduced the 2019 definition and algorithm of the Asian Working Group for Sarcopenia (AWGS) to assess the prevalence of sarcopenia in a substantial community-dwelling elderly population. Their study involved a cross-sectional data analysis of a cohort study with 2123 ambulatory older adults aged 70 to 84. A comprehensive array of physical function assessments was undertaken, encompassing handgrip strength, usual gait speed, the 5-times-sit-to-stand test, the timed up-and-go test, and the SPPB. The screening process for sarcopenia, within a case-finding assessment, involved the meticulous consideration of calf circumference (CC), the SARC-F questionnaire, and the amalgamation of SARC-F with CC (SARC-CalF). Employing the AWGS 2019 algorithm, the study discerned varying degrees of risk for sarcopenia among participants, revealing percentages of 43.5%, 7.5%, and 26.0% based on CC, SARC-F, and SARC-CalF, respectively. The results suggested that, based on the AWGS 2019 diagnostic criteria, screening for potential sarcopenia in community-dwelling individuals aged 70 to 84 may be more accurate when utilizing CC and SARC-CalF, as opposed to relying solely on the SARC-F questionnaire.

Savoie et al. [30] have innovatively automated the Timed Up and Go (TUG) test by utilizing a primary RGB video camera, without the need for additional depth sensors. This approach leverages contemporary advancements in computer vision technology. Thirty healthy individuals were videotaped while conducting numerous trials of the TUG test at 3 and 1.5 meters using a Kinect V2 and a conventional video feed. They employed deep learning algorithms to extract global 3D skeletons quite similar to those produced previously only using Kinect-based RGBD.

To improve the prediction of the risk of falling, Buisseret et al. [31] have developed a technique integrating clinical evaluations with motion capture sensors. Additionally,

they evaluated AI's capacity to forecast fall risk using only sensor raw data. They have demonstrated that combining the TUG test findings with gait variability indicators from a six-minute walking test enhances the capacity to forecast the risk of falling.

Sarcopenia is a condition characterized by a rapid loss of skeletal muscle and an accompanying deterioration in functional ability. Over 60-year-olds worldwide make up around 13% of those who are affected. Exercise prescription, together with the use of proper dietary techniques, are the mainstays of managing and preventing sarcopenia. Dent et al. [32] described age-related (primary) sarcopenia diagnostic and case-finding/screening techniques used in clinical practice and research. This evaluation also assessed each diagnostic and case-finding tool's strengths and flaws, as well as its accuracy in foretelling poor clinical outcomes and patient reactions to prospective treatments.

Using machine learning classifiers, Ko et al. [33] have conducted research to predict sarcopenia in older females through measurements of physical activity performance. They performed the experiment using the TUG test and the 6-minute Walk Test (6mWT) while wearing a single IMU to assess the physical performance of the elderly.

Elderly fall risk is frequently calculated using the TUG test. Incorporating general resident characteristics with the kinematic data obtained with a single inexpensive IMU during TUG can increase the precision of fall risk prediction, as demonstrated by Dierick et al. [34]. Data was gathered during the experiments using inertial sensors.

The Timed Up and Go (TUG) test is a widely recognized assessment of overall functional mobility, gauging an individual's proficiency in activities such as transferring, walking, and changing directions. As outlined by Dhar et al. [35], the TUG test serves as another means to evaluate muscle performance and functionality. In this test, the patient stands up from a chair, covers a distance of three meters, turns around, walks back, and then sits down. The customary duration for completing the Timed Up and Go (TUG) test is under 10.2 seconds, signifying a typical performance benchmark. Intriguingly, when examining the Western population, a distinctive trend emerges, revealing a protracted average TUG time of approximately 12.3 seconds. This observation underscores a notable divergence in the execution of the TUG test between different demographic groups.

An iPhone app to identify pre-frailty and sarcopenia syndromes in older persons living in the community has been developed by Montemurro et al. [36]. To measure sit-to-stand muscular strength, the video was employed.

2.4.2. Fall Prediction Through Functional Mobility Assessments

The assessment criteria for sarcopenia are summarized in Table 2.5, emphasizing physical performance, reduced muscle mass, and poor muscular strength. Low muscular strength is indicated by a grip strength of less than 27 kg for males and fewer than 16 kg for females, according to the EWGSOP2 (European Working Group on Sarcopenia in Older People) standards. Low muscle mass is defined as less than 20 kg

for males and less than 15 kg for females. Gait speed (0.8 ms^{-1}) and the TUG time (20 seconds) measure physical performance. The SDOC (Sarcopenia Definition and Outcomes Consortium) standards place a strong emphasis on muscle mass, with male and female cutoff weights of less than 35.5 kg and 20 kg, respectively. The same gait speed (0.8 ms^{-1}) is maintained, and the TUG time is not given. The AWGS standards also consider poor muscular strength, with values less than 28 kg for males and fewer than 18 kg for females. These cutoffs are less than 7 kgm^{-2} for males and less than 5.7 kgm^{-2} for females. Gait speed (1.0 ms^{-1}) and the 6-meter walk test are used to measure physical performance, showing differences in the standards employed by various organizations to diagnose sarcopenia.

TABLE 2.5: MUSCLE MASS, MUSCLE STRENGTH, AND PHYSICAL PERFORMANCE FOR SARCOPENIA

Criteria	Low Muscle Mass	Low Muscle strength	Physical Performance	
		Hand Grip	Gait Speed	TUG Time
EWGSOP2	M: <20 kg F:<15 kg	M: <27 kg F:<16 kg	≤0.8 ms^{-1}	≥ 20 s
SDOC	-	M: <35.5 kg F: < 20 kg	≤0.8 ms^{-1}	-
AWGS	M: <7 kg/m^2 F:< 5.7 kg/m^2	M: <28 kg F: < 18 kg	≤1 ms^{-1} (*)	-

*Note. M: Male, F: Female, * 6m Walk Test*

According to prior studies and recommendations, Table 2.6 lists the detectable TUG time requirements for sarcopenia identification. Two cut-off values, with TUG times of > 10.20 seconds and > 12.30 seconds, were recommended by Choo et al. [27], suggesting probable sarcopenia. Martinez et al.'s [37] recommendation for a TUG time threshold for sarcopenia detection was 10.85 seconds. While Bischoff et al. [26] also indicated a TUG time of 20.0 seconds for the diagnosis of sarcopenia, the EWGSOP advocated a more cautious threshold of 20.0 seconds. Finally, a lower threshold of 7.50 seconds was suggested by Filippin et al. [38]. These different cutoff values demonstrate the range of standards and criteria used to evaluate sarcopenia, emphasizing the significance of knowing the precise criteria used in assessing research findings in this area.

TABLE 2.6: SARCOPENIA DETECTABLE TUG TIME PRESENTED BY PREVIOUS RESEARCHERS AND GUIDELINES

Reference/Institute	Cut-Off TUG time/(s)
Choo et al. [39]	> 10.20
Choo et al. [39]	> 12.30
Martinez et al. [40]	≥ 10.85
EWGSOP	≥ 20.00
Bischoff et al. [41]	≥ 20.00
Filippin et al. [42]	≥ 07.50

Table 2.7 lists the gait speed cut-off values for sarcopenia as determined by several earlier studies and recommendations. Cruz-Jentoft et al. [43] created a gait speed threshold of 0.8 ms^{-1} to signify sarcopenia-related impaired physical function. A walking speed of less than 0.8 ms^{-1} was accepted by Shaikh et al. [44] as the standard for diagnosing sarcopenia.

TABLE 2.7: GAIT SPEED FOR SARCOPENIA BY PREVIOUS RESEARCHERS AND GUIDELINES

Reference	Cut-Off Gait Speed (m/s)	Description
Cruz-Jentoft et al. [43]	≤ 0.80	Poor physical performance related to Sarcopenia
Shaikh et al. [44]	< 0.80	considered as sarcopenia
Rathnayake et al. [45]	≤ 0.96	A cross-sectional study from Sri Lanka in middle-aged (20–40 years)
Studenski et al. [46]	≤ 0.80	-
EWGSOP/EWGSOP2	≤ 0.80	-
AWGS	≤1.00	For the 6m walk test

With a focus on middle-aged people (20–40 years old), Rathnayake et al. [45] conducted a cross-sectional research in Sri Lanka and established a gait speed threshold of 0.96 ms^{-1}. A walking speed of fewer than 0.8 ms^{-1} was also recognized by Studenski et al. [46] as symptomatic of sarcopenia. Furthermore, a gait speed of less than 0.8 ms^{-1} is advised as a diagnostic standard by the EWGSOP and its revised version (EWGSOP2). The 6-meter walk test has a threshold of 1 ms^{-1} that must be met to diagnose instances of sarcopenia, according to the AWGS. In clinical and research contexts, these gait speed cut-off values are crucial resources for evaluating and diagnosing sarcopenia.

2.4.3. Human Body Key Point Extraction Using BlazePose Algorithm

Compared to 2-D approaches, 3-D pose estimation gives a more complete and precise evaluation of body motions and postures. It enables the assessment of joint angles and locations in three dimensions, offering a more thorough insight into an individual's mobility. The "Vitruvian Man" by Leonardo da Vinci and BlazePose are two separates but connected ideas in art and technology. Figure 2.2 shows the 33-key points distribution in Leonardo's Vitruvian Man.

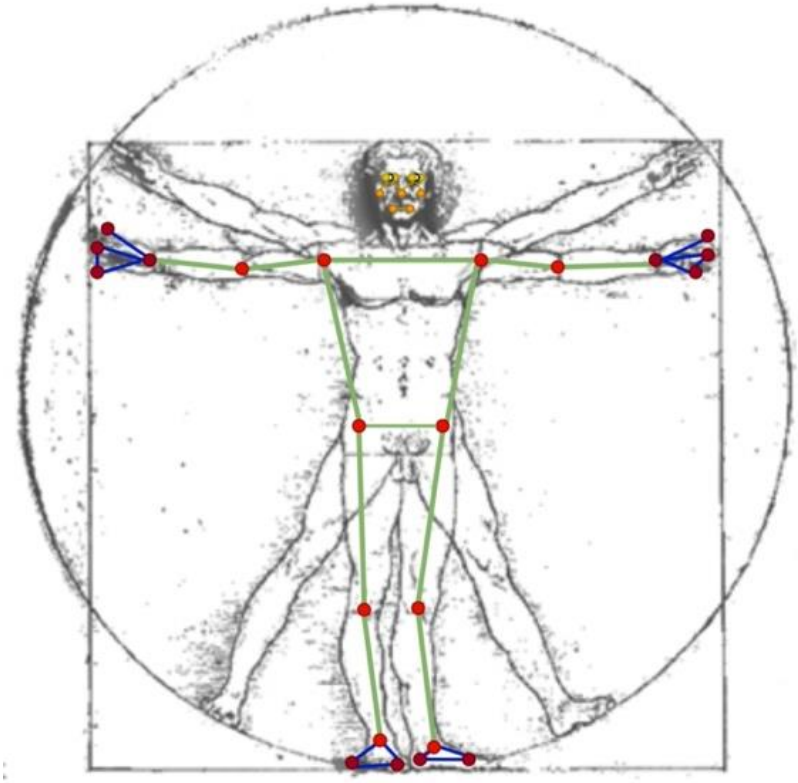


Fig. 2.2: Body landmark distribution in Leonardo's Vitruvian man

A machine learning technique called BlazePose can be applied to pose estimation, which entails finding and following the locations of various body components in an image or video. Google created this algorithm using a Deep Neural Network (DNN) architecture [47]. Figure 2.3 shows the critical landmarks of the human body, inference pipeline, and network architecture. The head, neck, shoulders, elbows, wrists, hips, knees, and ankles are just a few of the 33 critical places on the human body that the BlazePose algorithm can estimate in 2D and 3D space. This makes it an effective tool for examining posture and movement in people. The examination and treatment of sarcopenia, a disorder marked by the aging-related decrease of muscular mass and strength, is one possible use for BlazePose. For proper diagnosis and therapy, it is essential to accurately quantify muscle mass and function because sarcopenia is a significant cause of frailty and impairment in older persons.

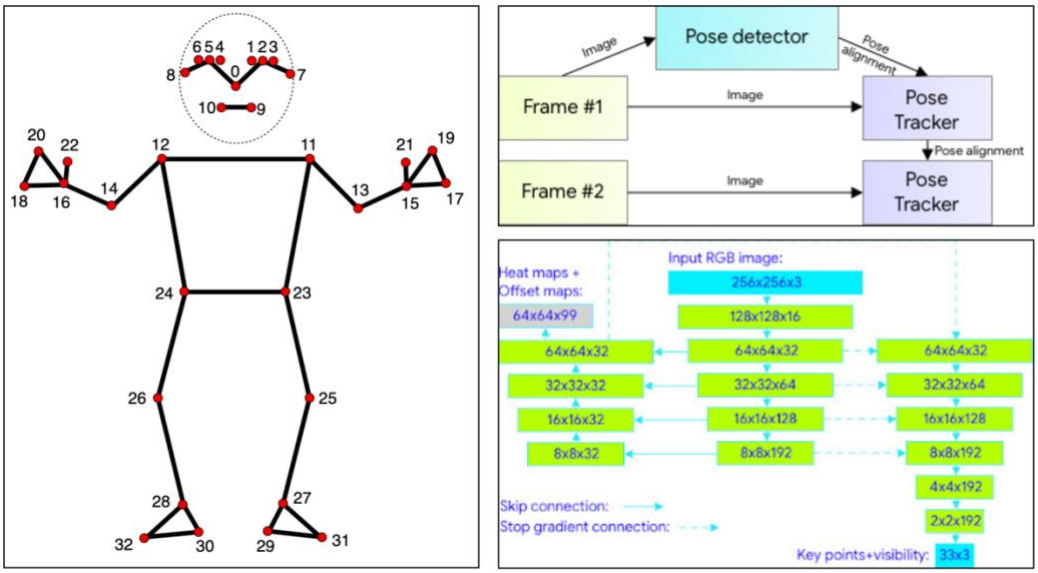


Fig. 2.3: Left: Body poses key landmarks, Right (top): Inference pipeline, Right (bottom): Network architecture. Adopted from [47]

Human key point detectors perform poorly because existing human key point extraction networks, such as OpenPose, AlphaPose, and OpenPifPaf, are fragile to dense crowd occlusion or human self-occlusion [48]. Therefore, Google developed the pose estimate method known as BlazePose to accurately forecast the 2D and 3D postures of the human body. It uses a two-step approach composed of a body detection module and a posture estimation module [49]. The BlazePose body detection module identifies the entire human body in an image or video. It determines the bounding box around the human body using a single-shot detector (SSD) architecture, an object detection model. This detection seeks to find the whole body rather than just the shoulder and hip centers. The body identification module's output is sent into BlazePose's pose estimation module, which uses it to anticipate further the major joints of the human body, including the shoulders, elbows, wrists, hips, knees, and ankles. It is based on Leonardo's Vitruvian Man. It makes predictions about the hip midpoint, the radius of a circle enclosing the entire body, and the inclination angle of the line joining the shoulder and hip midpoints. By leveraging the superset of the points utilized by BlazeFace [48], BlazePalm, and Coco [50], BlazePose presents a novel topology employing 33 key landmark points on the human body.

2.4.4. Summary of Literature Review

A thorough synopsis of the literature review on the subject of sarcopenia screening is given in Table 2.8, with an emphasis on the evaluation techniques used by various writers throughout the years. The research community has shown considerable interest in investigating sarcopenia, a phenomenon characterized by the age-related decline in both muscle mass and function. The important findings and methodology of the research done between 2011 and 2023 are highlighted in this table.

TABLE 2.8: SUMMARY OF LITERATURE REVIEW

Author(s)	Publication Year	Sarcopenia Screening Methodologies		
		TUG Test	Gait Speed	Fall Measurements
Stone and Skubic [51]	2011		×	
Martinez et al. [25]	2015	×		
Fillipin et al. [52]	2017		×	
Dubois et al. [26]	2017	×		
Tang et al. [53]	2018		×	
Bahat et al. [54]	2018		×	
Sanabria et al. [55]	2018			×
Sayer et al. [56]	2019			×
Ha et al. [57]	2019			×
Cruz-Jentoft et al. [27]	2019	×		×
Li et al. [58]	2019		×	
Addante et al. [37]	2019		×	
Phu et al. [28]	2020	×		
Kim and Won [29]	2020	×		
Lage et al. [59]	2020		×	
Bahat et al. [60]	2020		×	
Merchant et al. [61]	2020			×
Ozturk et al. [62]	2020			×
Ishida et al. [63]	2020			×
Savoie et al. [30]	2020	×		
Buisseret et al. [31]	2020	×		
Dent et al. [32]	2021	×		
Mo et al. [64]	2021		×	
Kim et al. [38]	2021		×	
Ko et al. [33]	2021	×		
Mohieldin et al. [65]	2021			×
Shin et al. [66]	2022	×		
Dhar et al. [35]	2022	×		
Dierick et al. [34]	2022	×		
Kim et al. [67]	2022		×	
Chen et al. [39]	2022		×	
Montemurro et al. [36]	2022	×		
Proposed System	2023	×	×	×

In conclusion, creating models utilizing the TUG test, gait speed test, and fall score assessment remains a waiting project despite adopting new criteria by WHO, EWGSOP 1 and EWGSOP 2 for automating sarcopenia screening. The development of models for the TUG test and gait speed has made some strides, but these techniques have primarily relied on wearable sensor-based methods, and they haven't yet been thoroughly studied regarding sarcopenia monitoring. There is an urgent need for a home testing model, given the novelty of the subject and the fact that sarcopenia is predominantly assessed using clinical mobility assessment techniques. The goal of this study is to present a feasible remedy for this field's current shortfall.

CHAPTER 3

AUTOMATING TUG AND 3M-WALK TEST USING VISION ATTENTIVE METHOD

This section discusses the proposed methodology of sarcopenia screening tools through the functional mobility of elders using TUG and 3m Walk tests.

3.1. TUG Activity Prediction and TUG Time Determination

Early diagnosis of sarcopenia-related mobility problems can be aided by forecasting TUG activities and measuring TUG time. Adopting timely interventions and strategies to stop future muscle loss and functional impairment depends on early identification.

Following the start of treatments, a person's improvement can be monitored throughout time by observing TUG activities and TUG timings. This enables medical practitioners to evaluate the success of therapies and alter them as necessary to improve outcomes and stop future functional deterioration.

3.1.1. Procedure

Researchers used a complex method to identify 2D and 3D poses of human bodies in pictures or videos by using the BlazePose algorithm. The result of this method was a complete set of coordinates that showed the exact location and orientation of the head, chest, arms, and legs, among other important body parts. The identification of Timed Up and Go (TUG) activities required taking into account a variety of body positions and motion paths, utilising the data these specific body markers offered.

The body landmark throughout the various activities is depicted in Figure 3.1. The figure demonstrates that during TUG exercises, the knee and hip angles are more significantly variable.

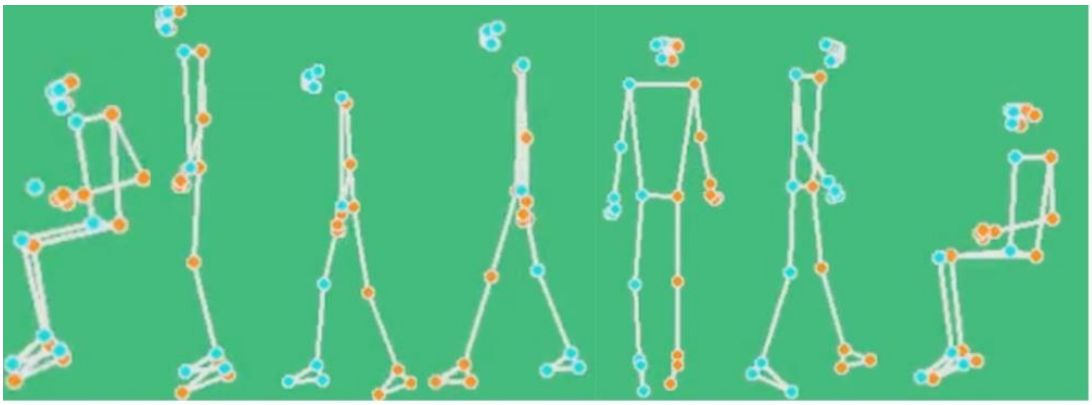


Fig. 3.1: Human pose extraction using landmarks

Figure 3.2 illustrates the body landmarks generated during the sitting activity. For this research, it is required to extract several body landmarks, such as shoulder (θ_S), hip (θ_H), and knee (θ_K), and the cosine rule was used to determine the Cartesian coordinates of each landmark.

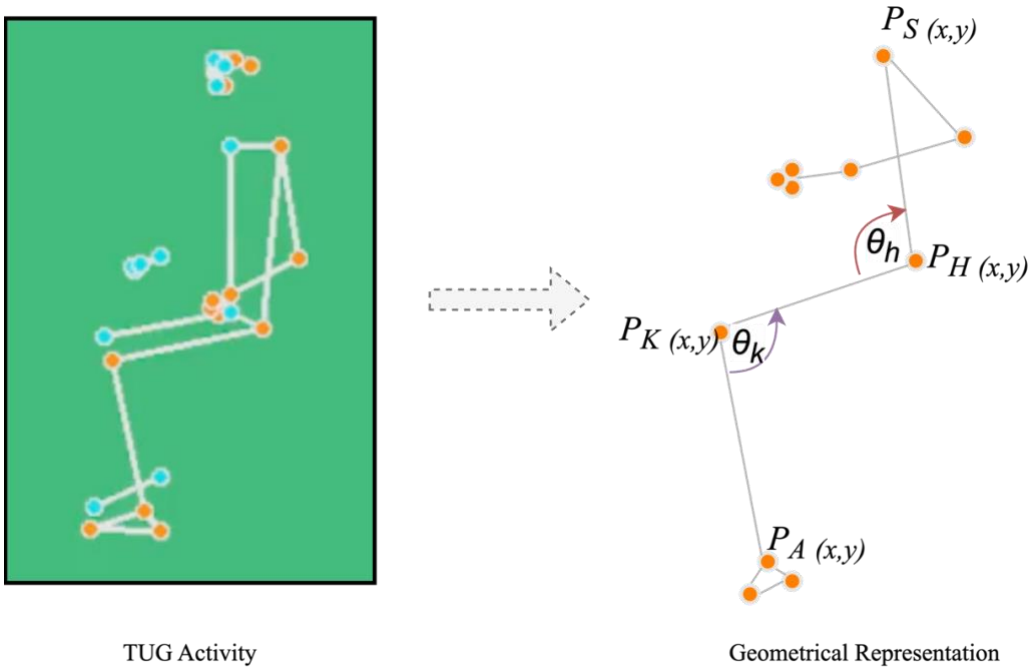


Fig.3.2: Generated body landmarks and its geometrical representation for the "sit" activity

In Figure 3.3, a detailed depiction unfolds, elucidating the intricate methodology employed for calculating knee angles through the application of cosine rules. The underlying equations, denoted as Equation 1, 2, and 3, intricately articulate the computation of distances between pairs of joints, employing the Euclidean distance metric for precise measurement.

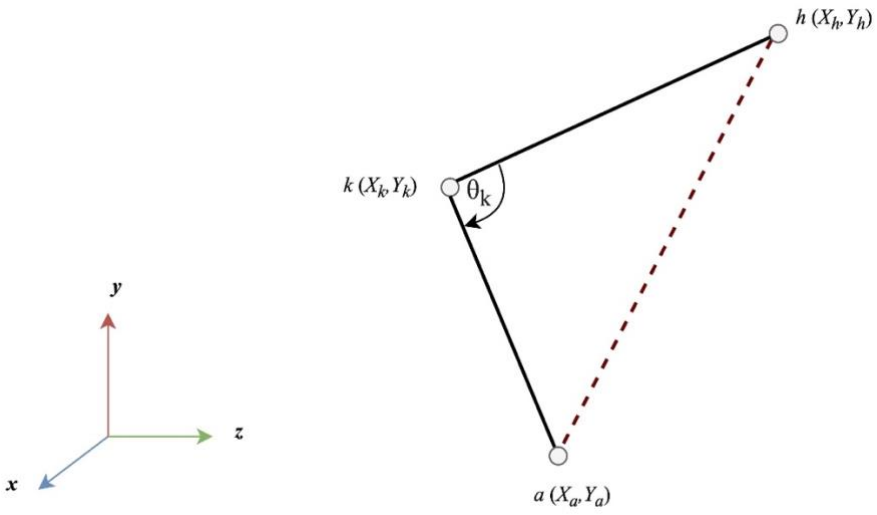


Fig. 3.3: Knee angle calculation using hip, knee, and ankle landmarks

$$d_{(a,k)} = \sqrt{(x_a - x_k)^2 + (y_a - y_k)^2 + (z_a - z_k)^2} \quad (1)$$

$$d_{(a,h)} = \sqrt{(x_a - x_h)^2 + (y_a - y_h)^2 + (z_a - z_h)^2} \quad (2)$$

$$d_{(k,h)} = \sqrt{(x_k - x_h)^2 + (y_k - y_h)^2 + (z_k - z_h)^2} \quad (3)$$

By employing the law of cosines as delineated in equations 1, 2, and 3, the knee angle (θ_K) was meticulously computed, revealing the intricate calculation process expounded in equation 4.

$$\theta_K = \cos^{-1}\left(\frac{d(k,h)^2 + d(k,a)^2 - d(h,a)^2}{2d(k,h)d(k,a)}\right), where\ 0 \leq \theta_K \leq \pi \quad (4)$$

The activity and direction prediction model is depicted in Figure 3.4. Utilizing the hip landmark's *z*-coordinate (*, *, z_H), the direction was established. Equation 4 was used to produce the model's angle computation. Angle computation results, hip (θ_H), and shoulder *y*-coordinates (*, y_S, *) were used to determine each TUG activity.

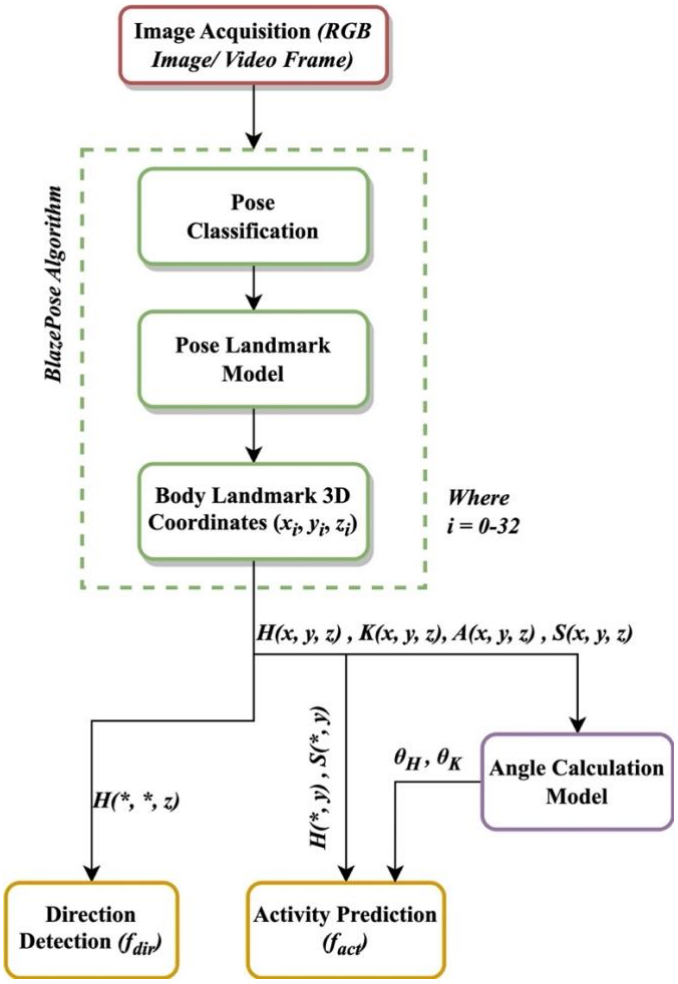


Fig. 3.4: The overall architecture of the TUG variable estimation model

Figure 3.5 shows the architecture of the TUG activity prediction model. The Random Forest (RF) machine learning (ML) algorithm was applied to a dataset with 4293 samples and four features to predict one of three classes. While developing decision trees, the Gini criteria were employed to gauge splits' quality.

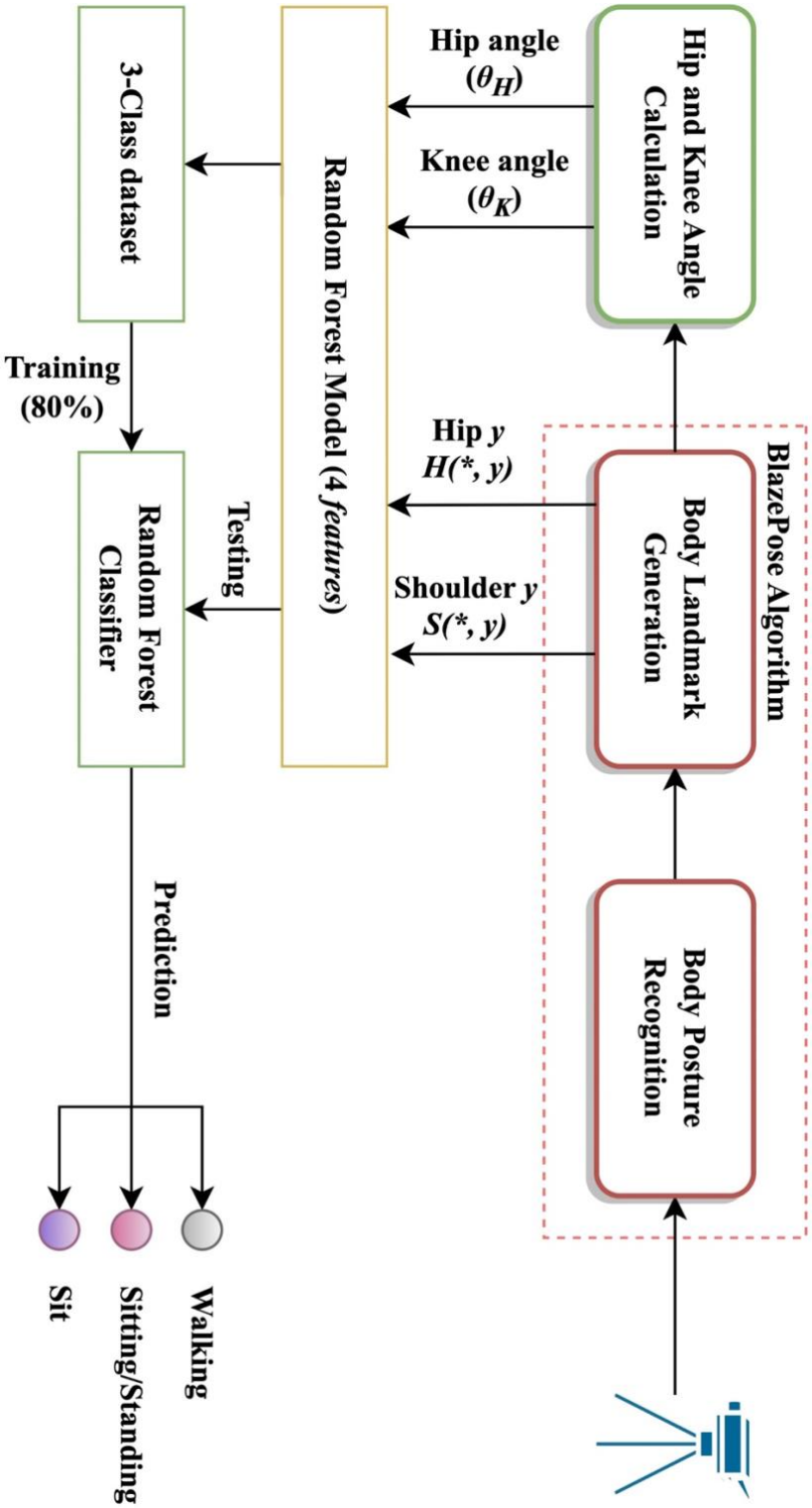


Fig. 3.5: Architecture of the proposed activity prediction model

Table 3.1 shows how various body landmark components rank regarding feature importance. The RF feature importance was utilized to identify the most suitable variables for TUG activity prediction. Table 5 depicts the feature importance of the training model. As shown in the table, more considerable variance occurred in the knee angle (48%), then 18% in the hip angle, 16% in the ankle *y*-coordinate, and 11% in the shoulder *y*-coordinate. As a result, the RF's input features, such as θ_K, θ_H, y_A, and y_S, were chosen.

TABLE 3.1: RANDOM FOREST FEATURE IMPORTANCE IDENTIFICATION

Feature landmark	Feature name	RF Feature importance (%)
θ_K	Knee angle	48
θ_H	Hip angle	18
(*, y_A, *)	Ankle *y*- coordinate	16
(*, y_S, *)	Shoulder *y*- coordinate	11
-	Other landmarks	7

3.1.2. Results and Discussion

This section discusses the results and analysis of the vision attentive-based TUG time estimation for determine the state of the functional mobility of the elders. The TUG activity was identified using angles (θ_i), *x*, and *y*-coordinates from various locations. The most influenced feature importance (see Table 3.1) from the input data was determined using the RF training model, which was then utilized to construct a new dataset. Initially, all θ_i, *x*, and *y*-coordinates were collected. Three classes (sitting/standing, walking, sit activity) were predicted using the created dataset. The improved training model used the Gini criteria and confusion matrix (see Figure 3.6), suggesting the proposed TUG activity prediction model achieved 91.2% accuracy in the RF.

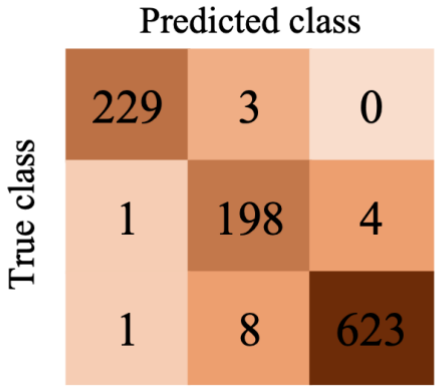


Fig. 3.6: Confusion matrix of the RF testing model

The vision attentive GUI was developed using Python for sarcopenia screening, as shown in Figures 3.7, 3.8, and 3.9. By utilizing the coordinates of the hip, knee, and ankle generated during Timed Up and Go (TUG) activities, the real-time knee angle for the given test case was precisely ascertained. Initially, a 3m test arena with seating needs to be built. The green line illustrates the 3m walk line, and the Red line shows the hip angle variation related to the TUG frame (f_{TUG}). The green lines on the 3m arena must always be followed.

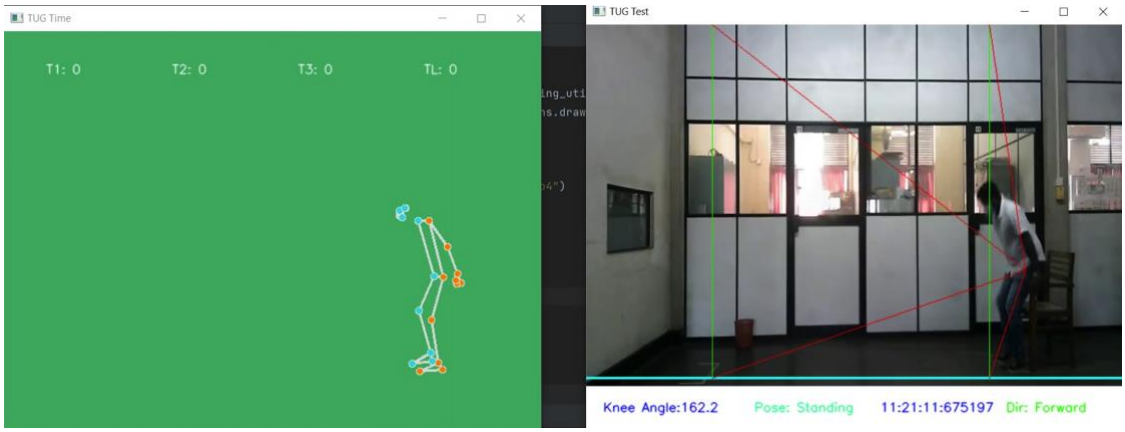


Fig. 3.7: The test case executes sit-to-stand in the TUG experiment

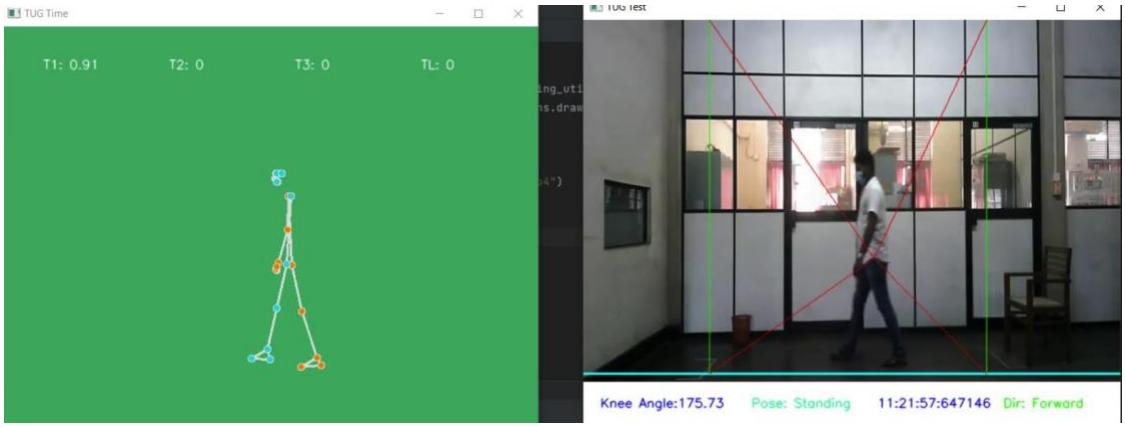


Fig. 3.8: The test case executes 3 meters forward walk in the TUG experiment

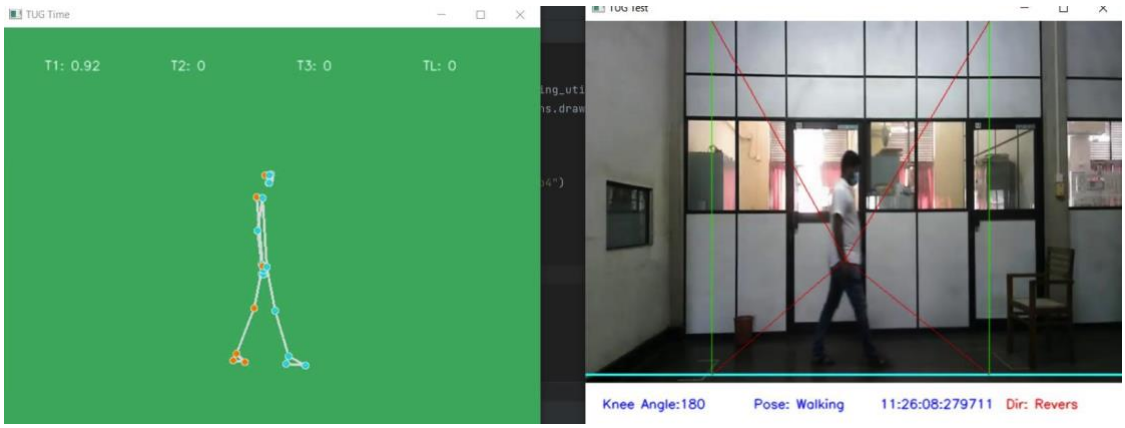


Fig. 3.9: The test case executes 3 meters backward walk in the TUG experiment

Figure 3.10 shows the computer view of the TUG experiment (GUI). Skelton was generated using the BlazePose model, which is identical to the human pose activities.

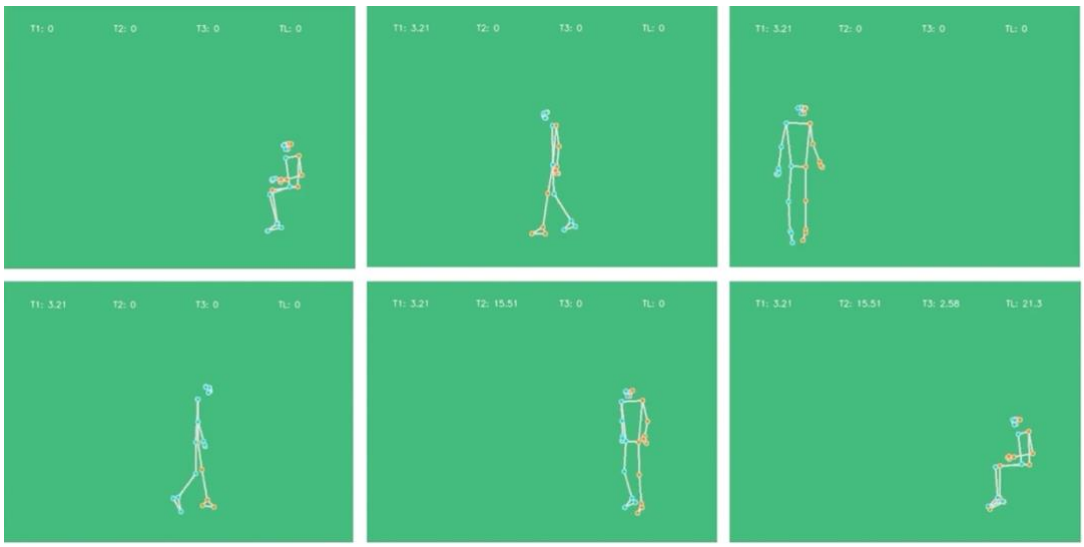


Fig. 3.10: Body Landmarks behavior during the experiment (Top row: Standing, walking forward 3m, turn 180 degrees, and Bottom row: walk reverse 3m, turn 180 degrees, sitting)

A detailed diagram describing the knee angle and *z*-direction fluctuations and criteria during the Timed Up and Go (TUG) test is presented in Table 3.2.

TABLE 3.2: ANGLE CRITERIONS FOR TUG ACTIVITIES

Knee angle (θ_K) variation	Activity	TUG movement identification
$115° < \theta_K < 170°$	Sitting down/getting up	-
$115° > \theta_K$	Sit	Start/End TUG test
$\theta_K > 170°$ and $Z_H > 0$	Forward walking	Chair-to-target walk
$\theta_K > 170°$ and $Z_H < 0$	Backward walking	Target-to-chair walk

Figure 3.11 describes measurements of the subject's knee angle (θ_K) and hip angle (θ_H) at various time intervals and associated positions such as sit, sitting, standing, and walking. The θ_K and θ_H values range from 90° to 180°, showing a wide range of mobility throughout the test time. The knee angle measurements can infer the participant's gait and balance since abnormal angles signify weakness or instability. The participant's movements and balance may be described in depth by the "sit" poses, which signify rest, and "walking" postures, which represent an activity. A pattern with a growing width appears in the graph as sarcopenia progresses in the test instances. This phenomenon helps us to understand how the functional deterioration linked to sarcopenia progresses. Interestingly, we found that people 70 years of age and older needed help—from an attendant or gait support—especially when they were doing sit-to-stand and stand-to-sit exercises.

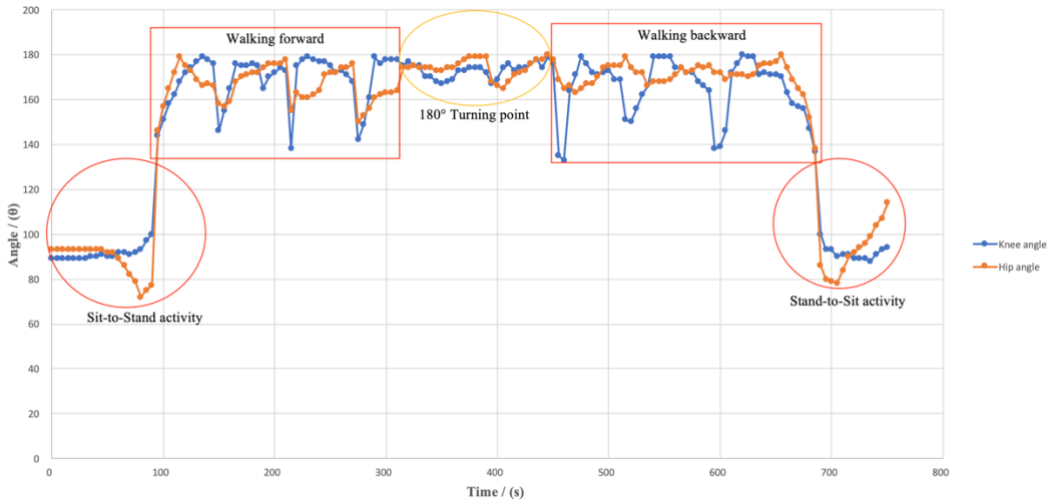


Fig. 3.11: Knee angle variation over TUG activities

An illustration of the complex range of knee angle variations seen in various test conditions is provided in Figure 3.12. The diagnosis of sarcopenia was made in Test Cases #1 and #2 after thorough physical examinations that included the traditional Timed Up and Go (TUG) test and an experiment with hand grip strength. Interestingly, the results revealed prolonged TUG times for these particular individuals, which is a prominent sign of severe sarcopenia. The difficulties in carrying out the "sit-to-stand" and "stand-to-sit" exercises were clearly displayed in the graph, highlighting the complexities of these motions in the setting of sarcopenia. Test Cases exhibiting minimal task performance were characterized by more pronounced and notable variations in knee angles, further underscored by the graph's representation of knee angle variation (refer to Figure 3.12), serving as a visual portrayal of this distinctive phenomenon.

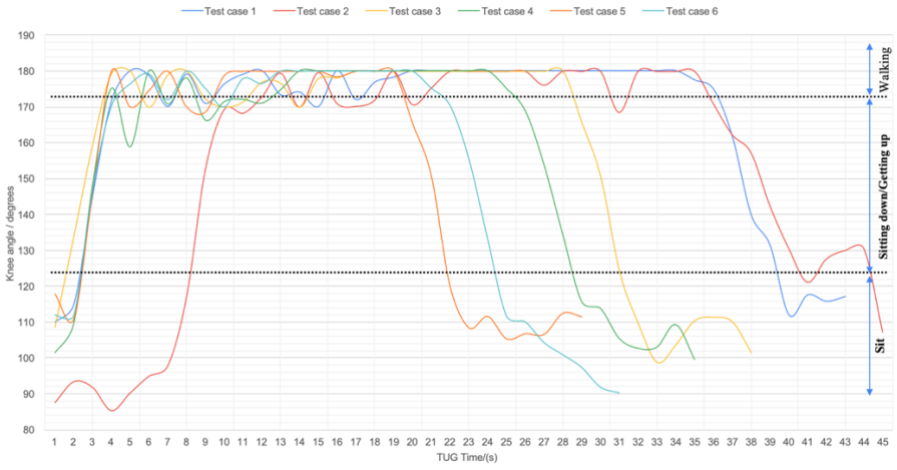


Fig. 3.12: TUG time Vs knee angle variation

Figure 3.13 displays the TUG time results using the proposed methodology versus the clinical approach (stopwatch). TUG system was tested with 33 test cases (F-61 %, M-39 %) in different age groups. Additionally, we saw that as Test Cases aged, their functional mobility decreased. As a result, TUG time increases (Test Case #10). This result underlines the critical influence of age on a person's capacity to carry out everyday tasks effectively. The lengthier TUG time in Test Case #10, as with many older persons, points to a reduction in functional mobility that may be impacted by aging-related variables such as muscular weakness, decreased joint flexibility, and reduced balance. The TUG time for the vision-based technique varies from 9.8 s to 65.2 s, whereas those for the traditional way range from 10.31s to 65.14 s. The average variation of the proposed system with the conventional method was 13.1 (±0.35).

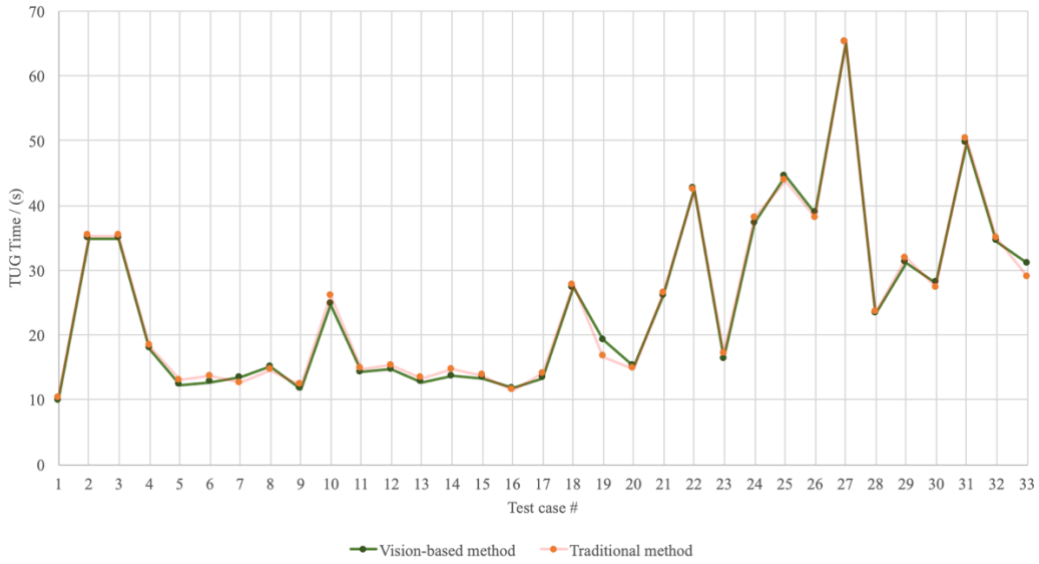


Fig. 3.13: TUG time measurement with both vision system and clinical method

The proposed approach demonstrated excellent results with an accuracy of 93.7 (±1.9) %, as seen in the graph. Overall, the data indicates that when evaluating TUG performance, the vision-based technique provided more reliable results than the conventional method. This is significant because it suggests that the vision-based technique can be a workable replacement for the traditional methodology, providing a more automated and objective means of assessing mobility.

3.2. Gait Speed Estimation Using 3m Walk Test (3mWT)

3.2.1. Procedure

Gait speed estimation was performed using the 3m Walk Test by embedding 3m forward walking activity in the TUG experiment. We considered the forward and backward 3-meter walk activities to evaluate the gait speed. During the Timed Up and Go (TUG) test, the time needed to complete the forward and backward 3-meter walks was noted. We combined the forward and backward walking speeds to calculate the average gait speed to reduce error.

Determining the hip pixel *x*-coordinate precisely is made possible by extracting the hip coordinate from the BlazePose model, an essential step in the gait analysis procedure. The study manages to align the spatial data from the BlazePose model with the targeted region of interest within the TUG frame by calculating the pixel distance to the hip pixel *x*-coordinate concerning the TUG frame. The defined region within the TUG frame, indicated by the green line, where the pixel distance to the hip pixel *x*-coordinate was measured, is most likely depicted in Figure 3.8. This graphic depiction makes it clear what the precise focus area is inside the TUG frame, guaranteeing that the analysis is carried out in a consistent and well-defined spatial context.

Figure 3.14 shows the proposed methodology of the distance calculation. Accordingly, time was calculated using a 3m forward and backward step time during the TUG experiment. The distance was measured with hip *x*-coordinates (x_H, *, *), calculated in the activity prediction model.

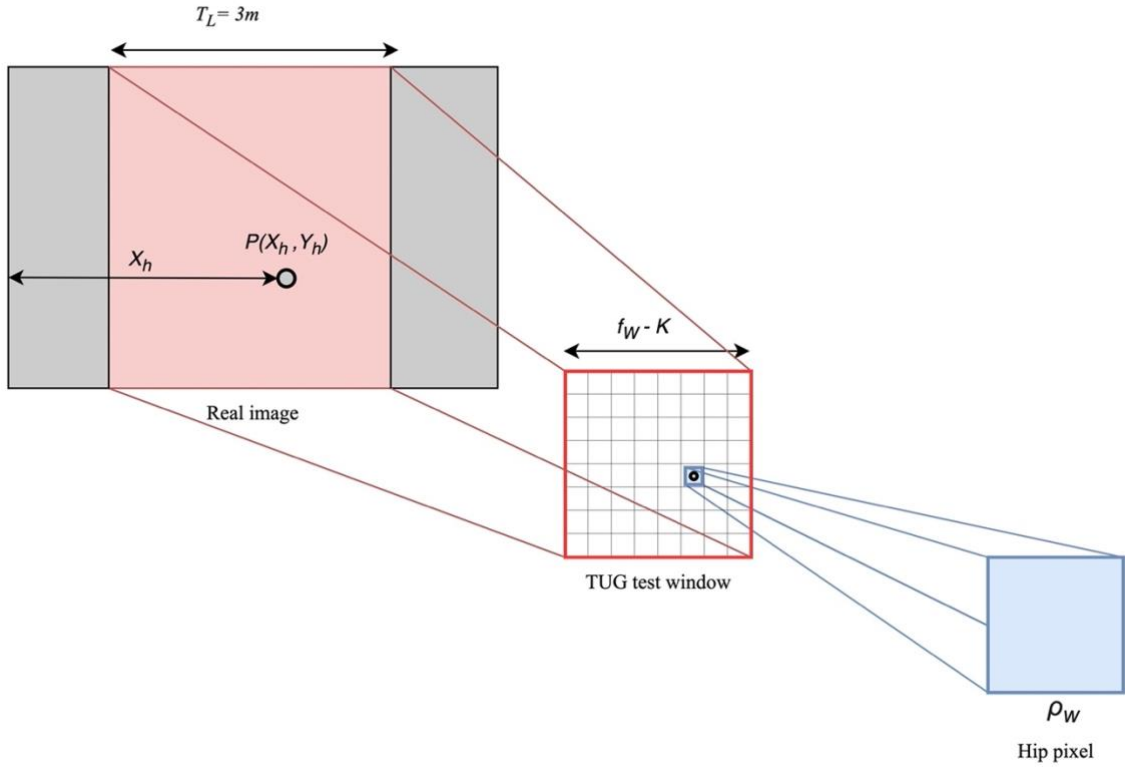


Fig. 3.14: TUG test embedded gait speed estimation model

Equation 5 represents the distance calculation mathematical model. Equation 6 describes the gait speed measurement of the proposed gait speed estimation model.

$$d = \left(f_{TUG} - p(X_h)\right) \times \left(\frac{T_L = 3}{f_W - K}\right) \quad (5)$$

$$v = \left(\frac{d}{t_{3m}}\right) \quad (6)$$

Where,

$p(x_h)$ – *Hip x-coordinate*

T_L – *3m (from 3m walk activity)*

F_W – *Frame width*

K – *Frame length variable*

v – *Gait speed*

t_{3m} – *Time taken to forward 3m walk in TUG test*

3.2.2. Results and Discussion

The gait speed measurement results from the 3m Walk Test are shown in Figure 3.15. As can be seen from the graph, test cases that tested positive for sarcopenia had an average gait speed that was less than 1.0 m/s. On the other hand, the analysis showed that the healthy subjects' average gait speed was greater than 1.0 m/s, suggesting a significant difference between the two groups.

Moreover, the graph indicates notable variations in the speed of gait between the starting and finishing points for each test case, indicating a marked instability in this set of data. Interestingly, Test Case #2 is an excellent example because it shows a person without sarcopenia whose functional abilities gradually decline over time, which affects their overall stability in the test.

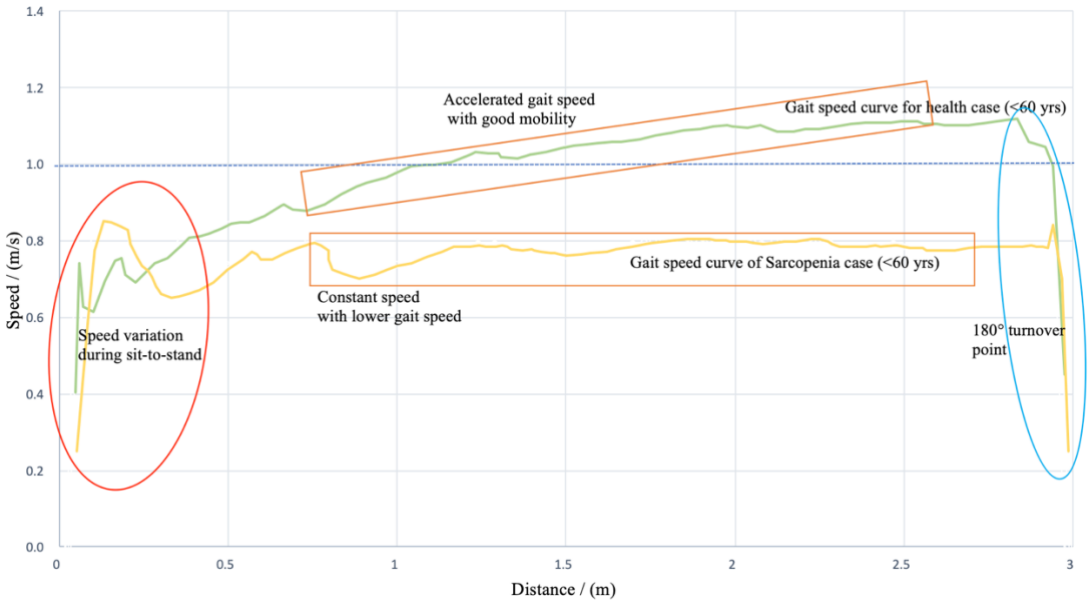


Fig. 3.15: Gait speed variation with healthy and abnormal mobilities

Figure 3.16, which shows the presentation of gait speed measurements taken during the 3m Walk Test, offers essential insights into the variations in gait dynamics between subjects who are healthy and those who have sarcopenia. The graph presents a clear

and concise representation of the different gait patterns noted in these two groups, with significant implications for our knowledge of mobility and functional health.

The data analysis indicates that the test cases who were diagnosed with sarcopenia, also known as the positive test cases, demonstrated an average gait speed that was less than 1.0 ms^{-1}. This suggests that their walking speed was significantly lower than that of the healthy subjects. The present study highlights the influence of sarcopenia on gait performance, implying that the ailment plays a noteworthy role in reducing the affected individuals' overall mobility and walking proficiency.

On the other hand, the average gait speed of healthy subjects, which was greater than 1 ms^{-1}, highlights the importance of normal muscle function and strength in preserving an effective gait pattern. This difference indicates that maintaining sufficient muscle strength is essential to sustaining a healthy gait and general functional independence, and it also emphasizes the critical role that muscle health plays in enabling optimal mobility.

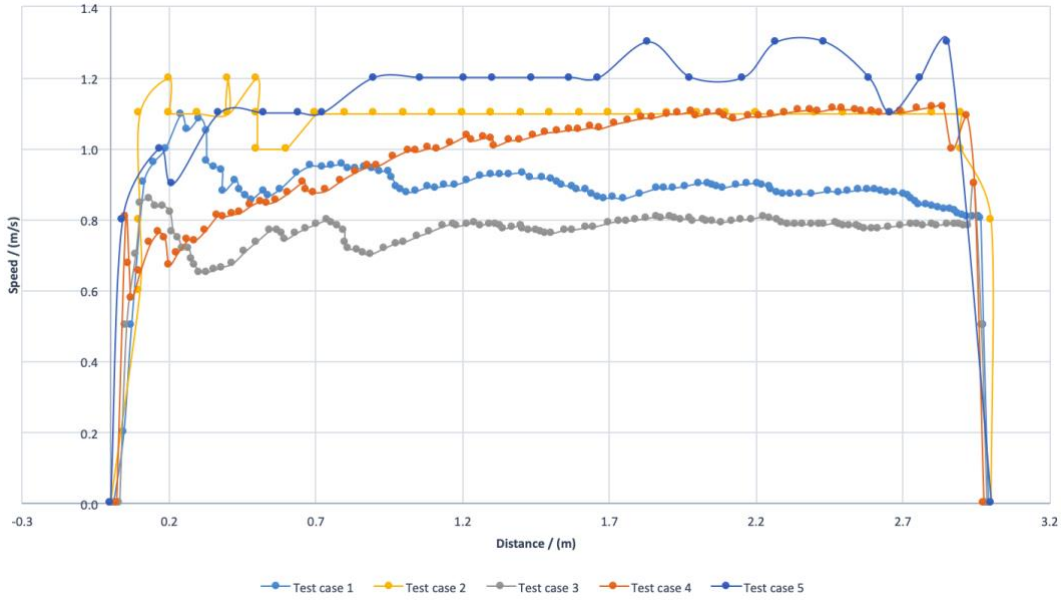


Fig. 3.16: Speed Vs. Distance in the 3m walk test

The significant fluctuations between the initial and final points on the graph also shed light on the instability seen in the test cases' gait patterns. This variability highlights how difficult it is for people with sarcopenia to maintain a consistent gait, which may increase their risk of falling and developing associated mobility problems. This finding highlights the necessity of focused interventions meant to increase stability and lower the chance of falls in sarcopenic patients.

Mainly, Test Case #2 provides a moving example of the intricacies involved in functional abilities over time. Even in the absence of sarcopenia, the person's overall stability during the 3m Walk Test is significantly affected by the gradual decline in their functional abilities. This case emphasizes the complex nature of mobility problems, implying that factors other than sarcopenia may also play a role in impaired gait dynamics and general functional decline.

Overall, Figure 3.7's extensive analysis of gait speed measurements illuminates the complex interactions between muscle health, gait performance, and overall functional abilities. These insights are critical for creating tailored care plans and targeted interventions that enhance mobility and maintain functional independence, especially for people who are at risk of sarcopenia and related mobility impairments.

CHAPTER 4

ESTIMATION AND MAPPING OF MUSCULAR STRENGTH WITH FALL SCORE

The implementation of this novel methodology has noteworthy consequences for the treatment of the elderly and the avoidance of injuries since it assesses a person's muscle strength while also offering vital information about their vulnerability to falls. This method provides a comprehensive framework for addressing the complex challenges associated with aging and maintaining functional independence. It represents a promising advancement in senior care by incorporating a multifaceted assessment of muscular strength and fall risk. The following conversation explores the step-by-step evolution of fall prediction techniques, highlighting the crucial connection between measuring muscle strength and identifying fall-related vulnerabilities. The study aims to improve the efficacy of fall prevention strategies tailored to the unique needs of the elderly population by enhancing our understanding of fall dynamics through the integration of vision-attentive modeling techniques.

A thorough understanding of the complex interactions between muscle strength, fall risk assessment, and stability margin identification is provided by the visual depiction of the proposed fall prediction and stability margin detection model in Figure 4.1. This graphical representation is an essential visual aid that clarifies the many moving parts of the suggested model and highlights how revolutionary it can be in terms of fall prediction and prevention in elderly care environments.

The state-of-the-art BlazePose body landmarks, a sophisticated computer vision methodology, provided the basis for developing the fall prediction system described in the chapter "Estimation and Mapping of Muscular Strength with Fall Score." By utilizing this technology's accuracy and precision, the system can track and identify essential body landmarks and conduct a thorough analysis of the various gait patterns that people exhibit.

After a thorough examination of these gait patterns, each person receives a customized assessment that results in the assignment of a fall score that takes into account their unique gait characteristics and movement dynamics. The predictive power and usefulness of the system were significantly increased when this fall score was paired with an assessment of the subject's grip strength. Interestingly, grip strength is a crucial measure of a person's total muscle and physical prowess, providing vital information about their strength and athletic potential.

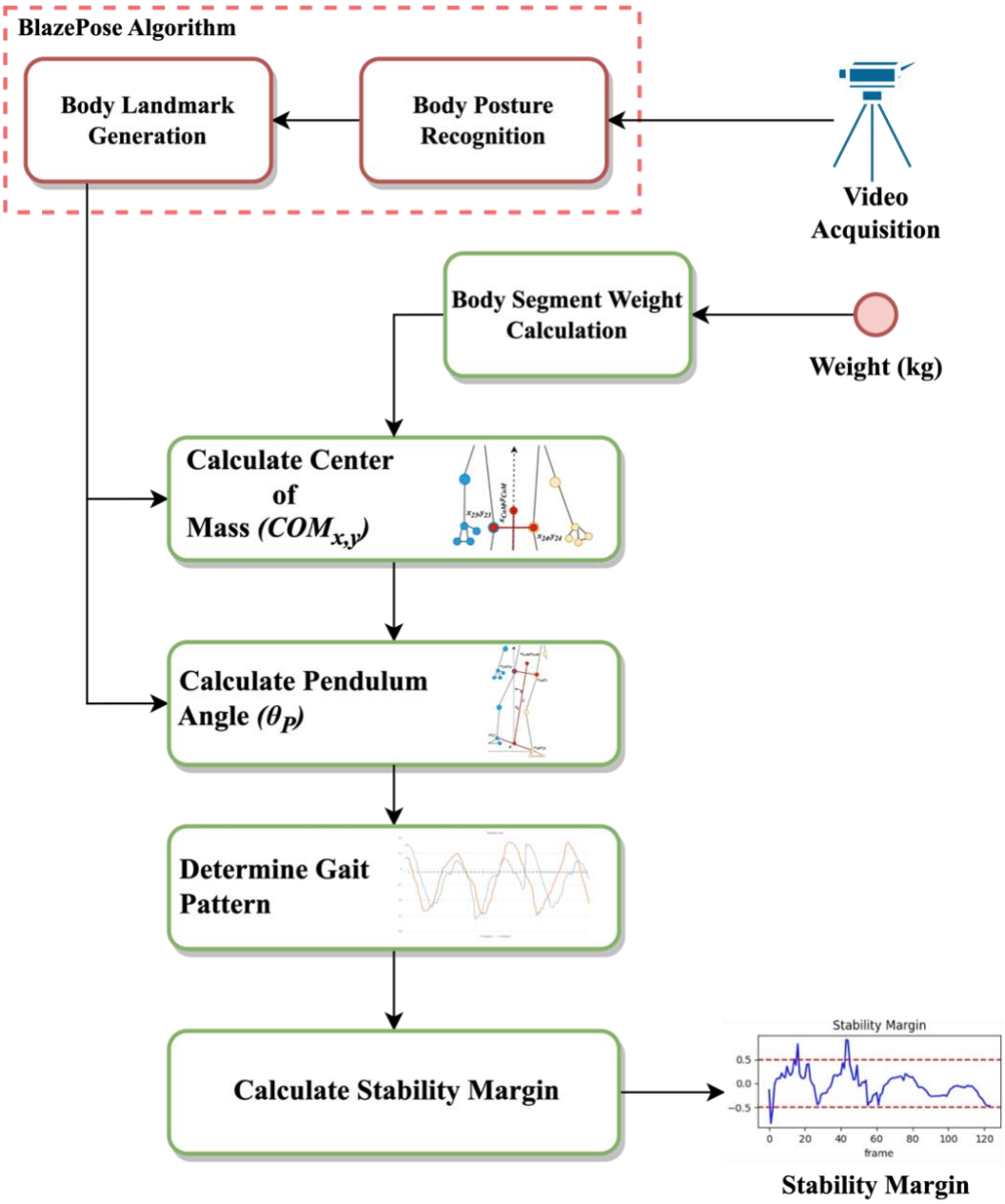


Fig. 4.1: Stability margin prediction model

By integrating accurate grip strength metrics with the fall score, this methodology provided a thorough assessment of an individual's fall risk, effectively delineating the complex relationship between muscle strength dynamics and fall risk. This detailed evaluation not only offers a comprehensive understanding of the various factors influencing fall incidents but also creates a robust framework for developing tailored interventions and targeted preventive strategies to reduce the risk of falls and improve overall health.

The BlazePose model was utilized to analyze body landmarks and posture, as illustrated in Figure 4.1. The study successfully evaluated the subject's overall body balance and weight distribution using the Centre of Mass's *x* and *y*-coordinates,

determined using body landmarks and body segment weight. Section 4.1 provides an in-depth explanation of the exact methodology used to calculate body segment weight.

4.1. Body Balance Estimation Using Inverted Pendulum Mechanism

Based on the body landmark data from BlazePose, the inverted pendulum model, a simplified depiction of the human body, may be utilized to simulate balance and forecast fall risk. The model presupposes that the body may be seen as an inverted pendulum, with the center of mass at the top and the feet at the base. To calculate the center of mass's location and pendulum's angle—all of which can be used to predict the likelihood of falling—the model uses the BlazePose body landmark data. Figure 4.2 shows the BlazePose body landmarks model used to predict falls.

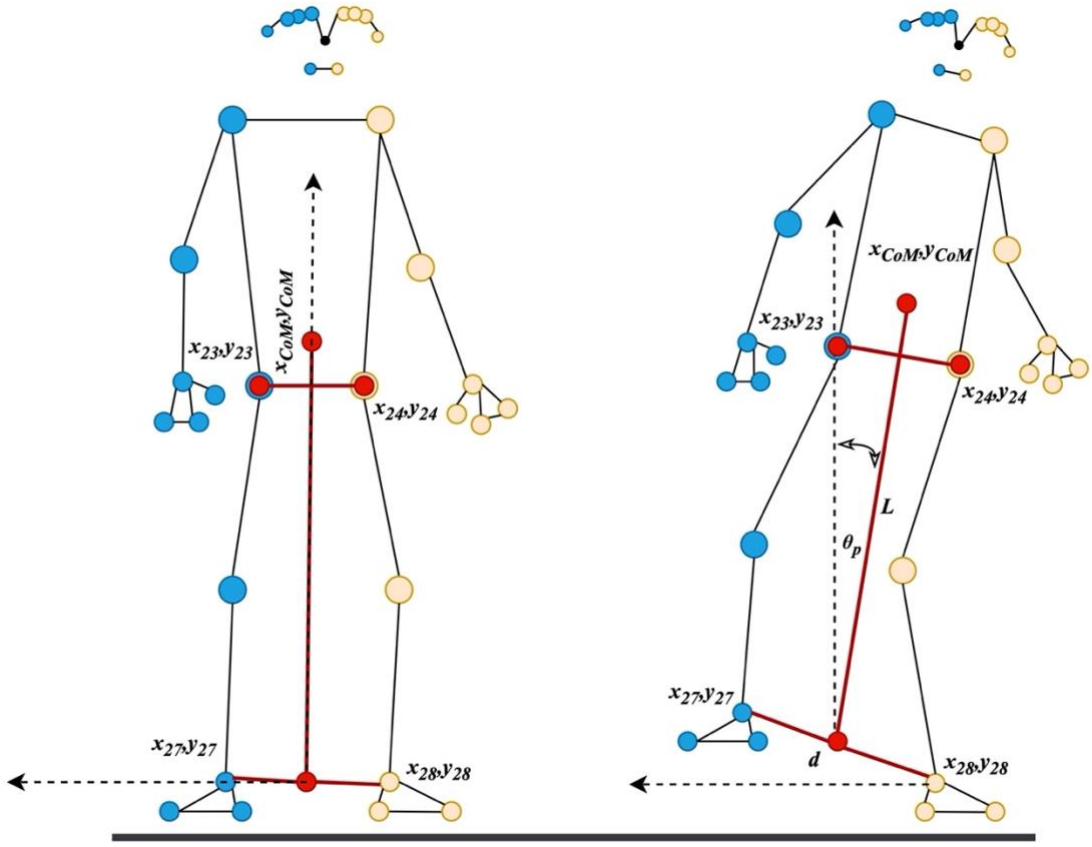


Fig. 4.2: BlazePose body landmarks model for fall detection

Using the BlazePose body landmark data, which offers the coordinates of many body landmarks, such as the hip joints and ankle joints coupled with body component weights, the location of the Centre of Mass (*CoM*) was determined. Assuming that the body can be represented as a collection of discrete point masses, the center of mass may be determined by averaging the locations of each body part, with each body part's weight being proportional to its mass. Equation 7 and 8 shows the *x* and *y*-coordinates of the center of mass.

$$x_{CoM} = \frac{(W_{LF} \times x_{28}) + (W_{RF} \times x_{27}) + \left(W_H \times \left(\frac{x_{24} - x_{23}}{2}\right)\right)}{(W_{LF} + W_{RF} + W_H)} \quad (7)$$

$$y_{CoM} = \frac{(W_{LF} \times y_{28}) + (W_{RF} \times y_{27}) + \left(W_H \times \left(\frac{y_{24} - y_{23}}{2}\right)\right)}{(W_{LF} + W_{RF} + W_H)} \quad (8)$$

The pendulum's length, or *L*, equals the distance between the feet from the center of mass. *L*'s value might change based on a person's height, weight, and other physical features. The distance between the center of mass and the feet was calculated using anthropometric parameters like leg length and the distance from the pelvis to the feet. Equation 9 describes the Center of Mass (CoM) position (x_{CoM}).

$$x_{CoM} = L \times \sin(\theta_p) \quad (9)$$

Equation 10 describes the pendulum angle to the vertical plane.

$$\theta_p = \tan\left(\frac{y_{28} - y_{27}}{x_{28} - x_{27}}\right) \quad (10)$$

Equation 11 describes the distance between proper ankle body landmarks and the left ankle body landmarks.

$$d = \sqrt{(x_{28} - x_{27})^2 + (y_{28} - y_{27})^2} \quad (11)$$

The distance between the center of mass's projection (X_{prj}) into the ground and the midpoint between both feet was considered the stability margin (SM). Equation 12 describes the X_{prj} of the pendulum.

$$X_{prj} = x_{CoM} - \left(\left(\frac{y_{28} + y_{27}}{2}\right) \times \sin\theta_p\right) \quad (12)$$

Equation 13 describes the stability margin of the model. A smaller stability margin indicates a higher risk of falling.

$$SM = X_{prj} - \frac{d}{2} \quad (13)$$

Where;

$\theta_p - Pendulum\ angle$

$L - length\ of\ the\ pendulum$

$x_{CoM,}\ y_{CoM} - x\ and\ y\ coordinate\ of\ the\ body\ center\ of\ mass$

$x_{23}, y_{23} - x\ and\ y\ ccordinate\ of\ the\ right\ hip$

$x_{24}, y_{24} - x\ and\ y\ ccordinate\ of\ the\ left\ hip$

$x_{27}, y_{27} - x\ and\ y\ ccordinate\ of\ the\ right\ foot$

$x_{28}, y_{28} - x\ and\ y\ ccordinate\ of\ the\ left\ foot$

$d - mid\ point\ between\ left\ and\ right\ foot$

$X_{prj} - Projection\ of\ the\ center\ of\ mass$

$SM - Stability\ margin$

$W_{LF} - Weight\ of\ the\ left\ foot$

$W_{RF} - Weight\ of\ the\ right\ foot$

$W_H - Weight\ of\ the\ hip$

4.2. Estimation of Body Segment Mass

Anthropometric data and standard tables of body segment masses can be used to estimate the mass and weight of each body part, which are necessary to calculate the weights of the left foot, right foot, and hip joint. The International Society for the Advancement of Kinanthropometry (ISAK) provides a standard protocol for measuring body composition and anthropometric dimensions, including body segment lengths and circumferences. This data can be used to estimate segment masses using regression equations developed from cadaver studies. The National Institute for Occupational Safety and Health (NIOSH) has published a set of equations for estimating segment masses based on body height and weight, as well as age and gender. These equations are based on data from a large sample of the US population and are commonly used in ergonomics and workplace design. The International Commission on Radiological Protection (ICRP) has developed a set of reference values for organ masses and tissue densities, which can be used to estimate segment masses based on medical imaging data. Figure 4.3 shows the body segment numbering.

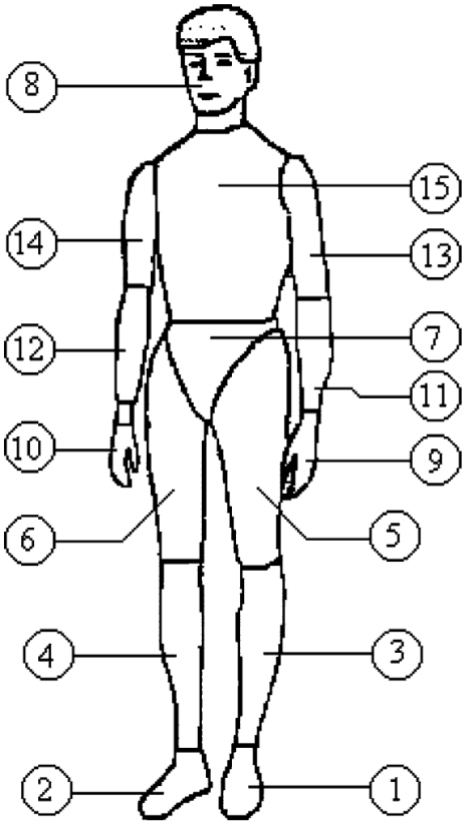


Fig. 4.3: Human body mass segment numbering (Adopted from [68])

The tables developed by Zatsiorsky and Seluyanov [68] provide segment masses for adults based on cadaver studies, as well as equations for estimating segment masses based on body height and weight. These tables are commonly used in biomechanics and can provide a reasonable estimate of segment masses for individuals with non-average body proportions. They also developed a set of regression equations to estimate the segment masses of the human body based on total body mass and body height. Moreover, Kaynakli et al. [69] introduced body segment mass fraction of total body mass. Table 4.1 shows the fraction of body segment mass proposed in [69].

TABLE 4.1: FRACTIONS OF BODY SEGMENT MASS

Body segments	Segment number	Fraction of total body mass (%)
Foot	1-2	1.45
Fibula	3-4	4.65
Thigh	5-6	10.0
Pelvis	7	8.48
Head	8	8.10
Hand	9-10	0.60
Forearm	11-12	1.60
Upperarm	13-14	2.8
Trunk	15-16	41.2

With the help of the mass of the previously mentioned body segments, this research was able to precisely calculate the Centre of Mass (CoM) for the participating human subjects. Utilizing this accurate body segment mass information, the proposed vision-based attentive methodology improves the ability to provide a non-invasive method of assessing and mapping muscle strength and fall risk. The potential of this approach to transform the assessment and mapping of critical health parameters while reducing the need for invasive procedures is highlighted by the significant advancement it makes in non-invasive assessment techniques.

4.3. Muscular Strength Vs. Fall Score Estimation

Within aging and mobility, grip strength and the risk of falling are closely related factors. They are maintaining one's ability to walk securely and confidently as one age becomes of the utmost importance. The crucial part that grip strength plays in determining and reducing the risk of falls in older adults has been acknowledged by several well-known health organizations, including the WHO, the AWGS, and the European Working Group on Sarcopenia in Older People (EWGSOP/2). These organizations routinely claim that a reduced grip strength among this population significantly increases the danger of falling.

4.4. Results and Discussions

Understanding and evaluating the stability of human locomotion heavily relies on the measurement of stability margins in various gait patterns. From regular, healthy gait to numerous aberrant patterns that neurological or musculoskeletal problems may cause, each gait pattern illustrates a distinct aspect of human mobility. Researchers and healthcare providers may learn much about the dynamic balancing and control processes of each gait pattern by examining stability margins across this range. Given that it gives precise data on how well someone can maintain their stability while walking, this information is essential for identifying and treating people with gait-related problems. Such assessments may also be used to develop rehabilitation plans and targeted therapies customized to specific gait abnormalities, enhancing the quality of life for persons with these illnesses. In general, the evaluation of stability margins in a variety of gait patterns is a crucial step in improving our comprehension of human locomotion and developing the gait analysis and rehabilitation area.

Figures 4.4 through Figure 4.8 illustrates the stability margin variation of different gait patterns of sarcopenia patient. A stable and balanced gait is characterized by a stability margin that is less than or equal to 0.3, which denotes a healthy state. People within this range have a low risk of falling and show steady, firm control over their movements. People who have a stability margin of between 0.3 and 0.7 are considered to need gait support because they have a moderate risk of falling. To avoid and reduce fall-related events and accompanying injuries, this group requires constant observation and potential intervention. The urgent need for thorough and quick actions was highlighted by a stability margin of 0.7 or above, which indicates a severe fall risk. People who fit into this group are at a high risk of suffering severe fall-related injuries. Thus, they need urgent care and help to keep them safe.

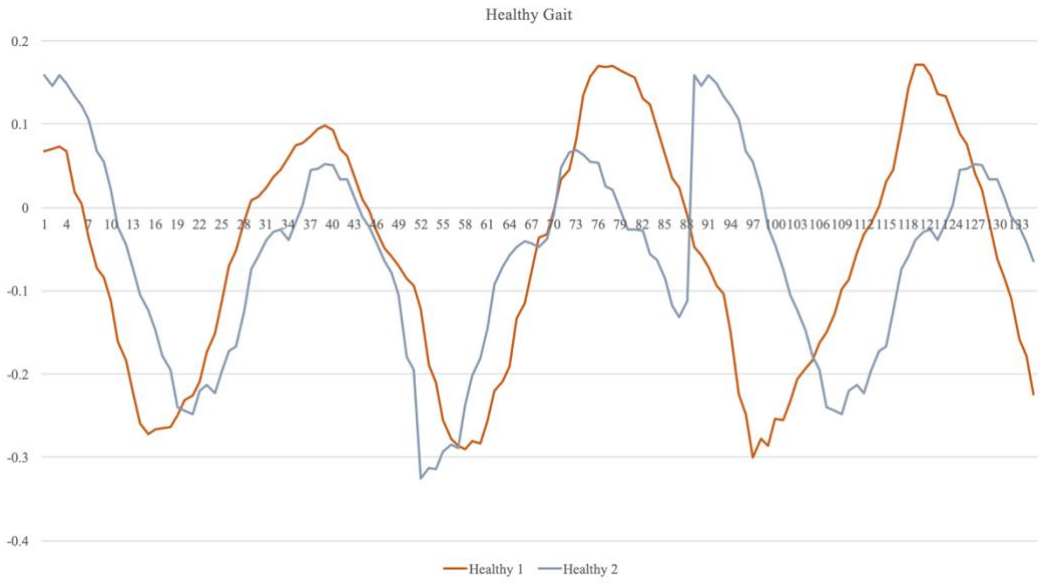


Fig. 4.4: Stability margin of the healthy gait pattern

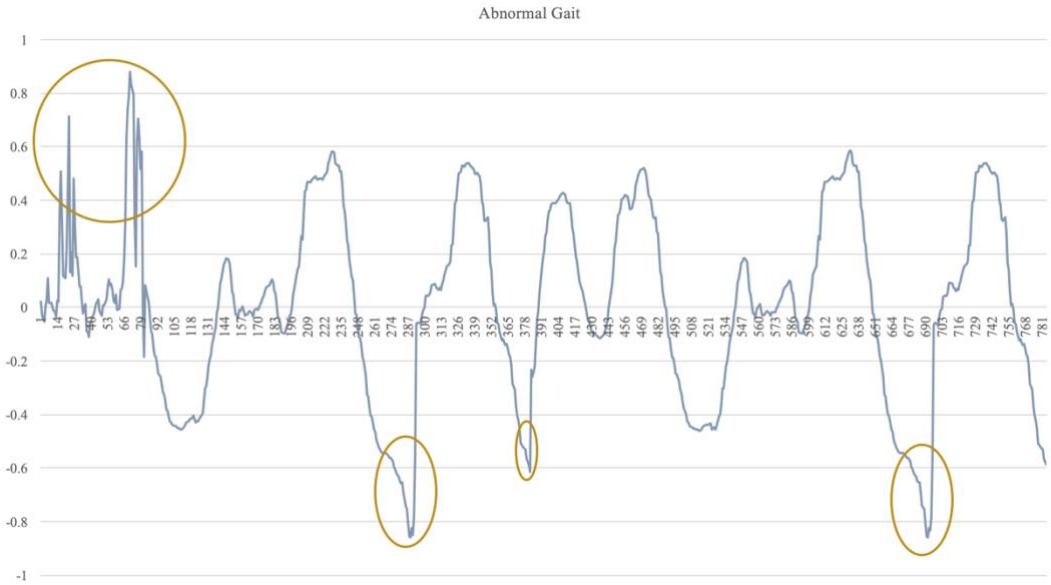


Fig. 4.5: Stability margin of the abnormal gait pattern

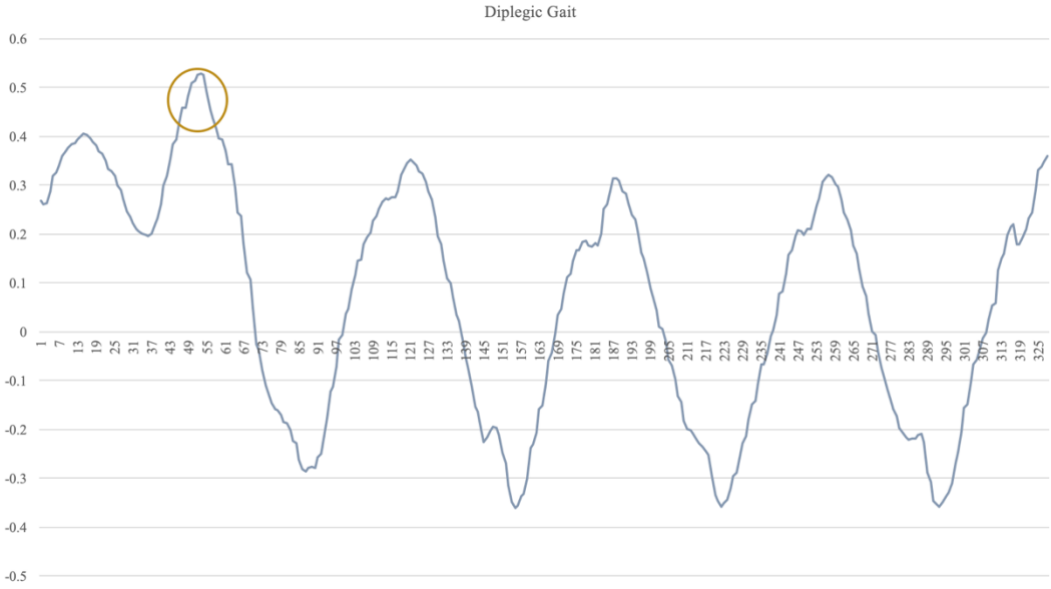


Fig. 4.6: Stability margin of the diplegic gait pattern

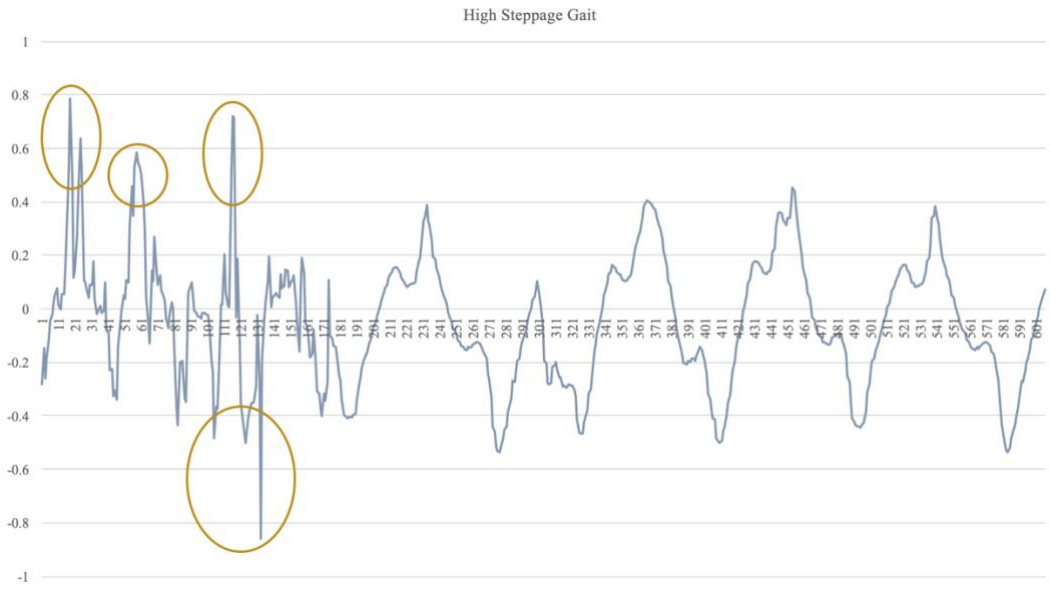


Fig. 4.7: Stability margin of the high stepping gait pattern

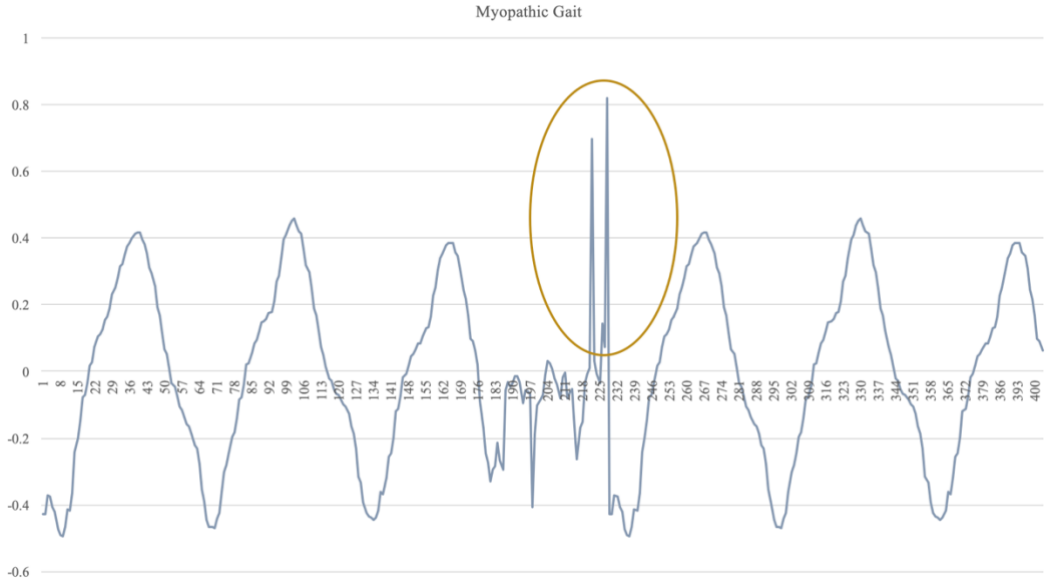


Fig. 4.8: Stability margin of the myopathic gait pattern

Figure 4.9 shows the relationship between the stability margin and prominent grip strength. This graph unequivocally shows that a more excellent SM score is associated with a higher chance of falling. On the other hand, a weaker grasp indicates a more significant chance of falling. The graphical illustration highlights the crucial role that grip strength plays in predicting falls in aging populations. It also provides valuable information for determining thresholds for fall risk assessment. Notably, a vital criterion for diagnosing an increased fall risk is an SM score over the 0.3 level. When SM rises beyond 0.7 after this time, the danger of falling is considered significant. The association between grip strength and fall risk is further supported by the fact that these higher SM scores also frequently correspond with lower grip strength readings. These

findings highlight the value of grip strength testing as a critical tool for supporting older people's safe and independent movement.

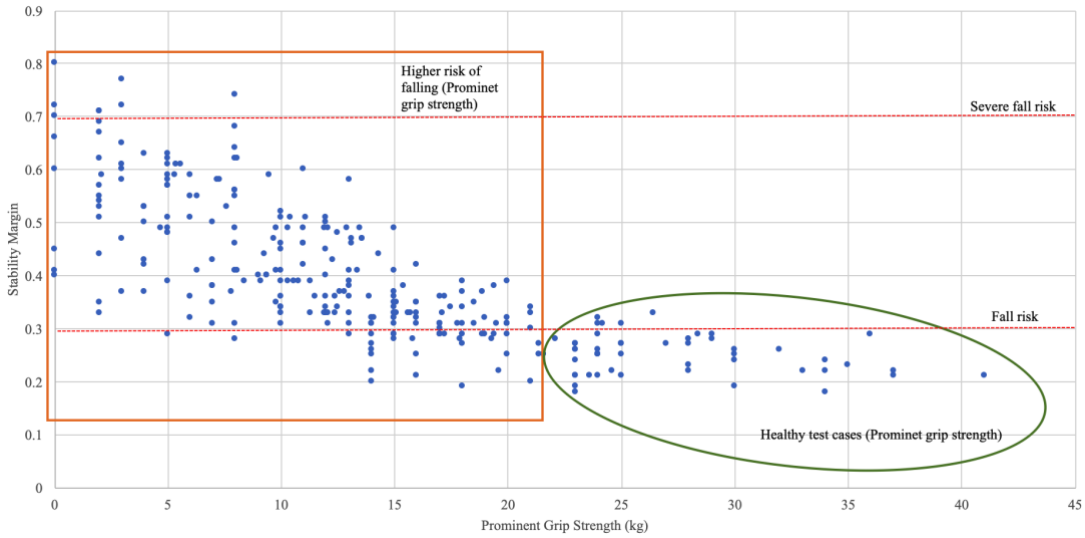


Fig. 4.9: Relationship between stability margin (SM) and prominent grip strength

The method enables healthcare professionals and patients to proactively assess and reduce fall risks by setting these separate levels. Such a comprehensive approach to evaluating fall risk is essential for encouraging early interventions and specialized preventative measures to safeguard people, especially those at risk for falls, such as the elderly and people with specific medical problems.

CHAPTER 5

VISION ATTENTIVE-ENABLED SARCOPENIA SCREENING MODEL

The development of the Sarcopenia screening tool/GUI will be discussed in this section. Its objective is to make sarcopenia evaluation in a domestic setting easier. The procedure of measuring and evaluating functional mobility assessments using a visual method will be simplified by integrating the proposed tool.

5.1. Development of TUG Test, 3m-Walk Test, and Fall Prediction Enabled Sarcopenia Screening Tool

To provide real-time evaluation and analysis of human motions, the Python-based health monitoring system described above integrates several technologies. This system showed a complex usage of OpenCV, MediaPipe, and TensorFlow to monitor particular health measures and assess stability levels by leveraging Python's powerful robust and the PyCharm IDE.

Python, a flexible and popular programming language, is the system's basis. A productive and well-organized workflow is made possible by the flexibility of Python and the PyCharm Integrated Development Environment (IDE). The system makes use of several libraries, including OpenCV, MediaPipe, Numpy, Datetime, Time, Joblib, Math, TensorFlow, and Tkinter, which together allow the system to collect, handle, and examine health-related data.

The starting phase gets the environment ready for the subsequent steps. It is necessary to import the appropriate libraries, machine learning models, and variables. The system's ability to employ machine learning to make precise predictions was demonstrated using Artificial Neural Networks (ANN) and Support Vector Machines (SVM). The videos were captured using OpenCV, which was required for extracting test subject video samples for analysis. The MediaPipe library's Blaze posture detector was given specific detection and tracking confidence levels.

Figure 5.1 displays the GUI created for entering demographic data. The operator must enter crucial information into the system, such as gender, age, height, and weight. These particular variables were used directly as features for the ANN's input features. Notably, the weight information was used to determine the mass of the body segments, which was necessary to determine the stability margin (SM). This interactive interface acts as a vital entry point for incorporeity, pointing significant participant data into the system providing a thorough and expedited assessment of numerous health metrics and risk factors.

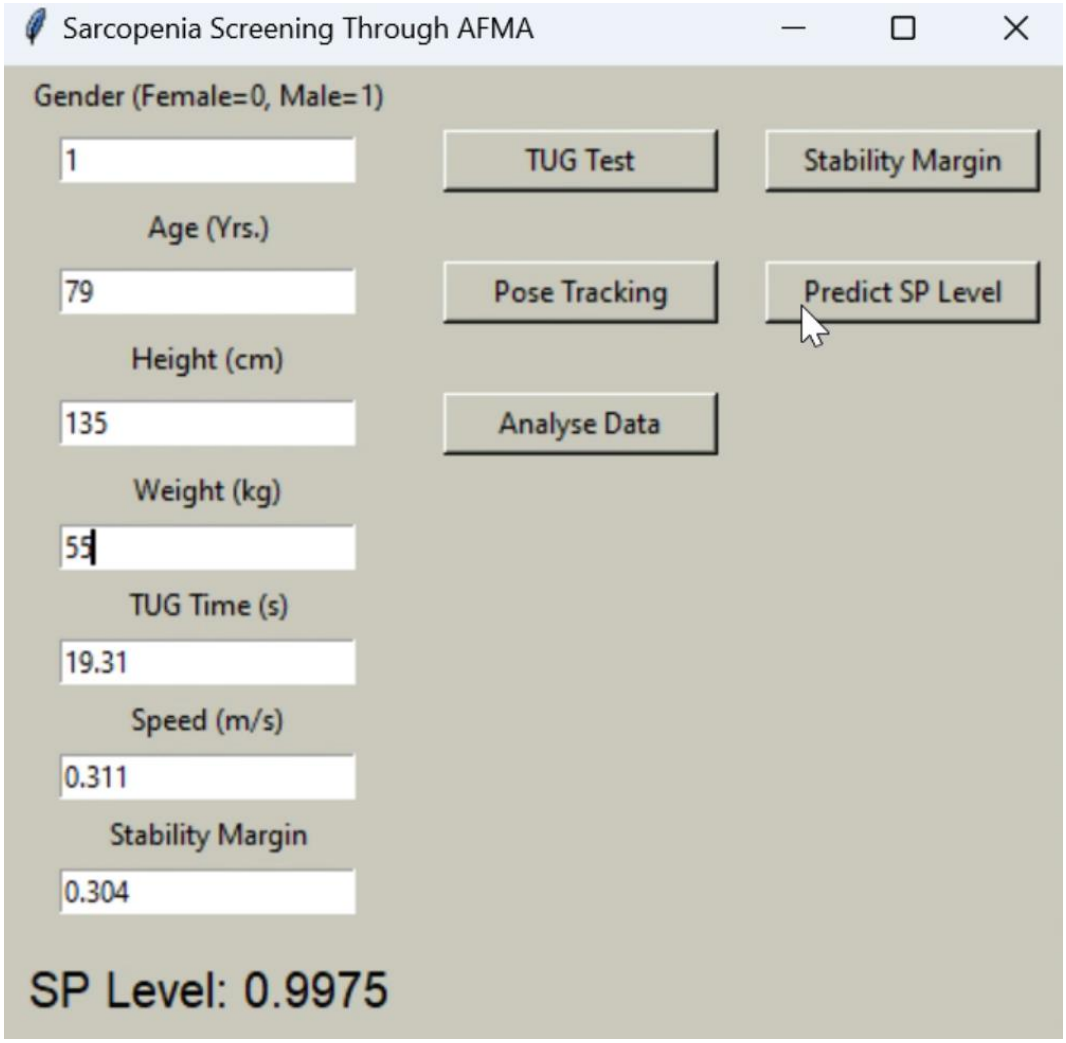


Fig. 5.1: Demographic information feed GUI

The developed vision system for calculating gait speed and duration Up and Go (TUG) duration is shown in Figure 5.2. The figure presents a selection of test scenarios from the TUG trials, some of which included applying gait assistance equipment. The green line represents the TUG arena, while the red lines show the hip coordinate about TUG frame reference points.

Because the BlazePose model removes noise from the source picture, it provides stable results even in low light. This makes it an excellent choice for the TUG time estimate. Nevertheless, in this case, keeping the lighting constant is seen to be the practice for ensuring accuracy and peak system performance.

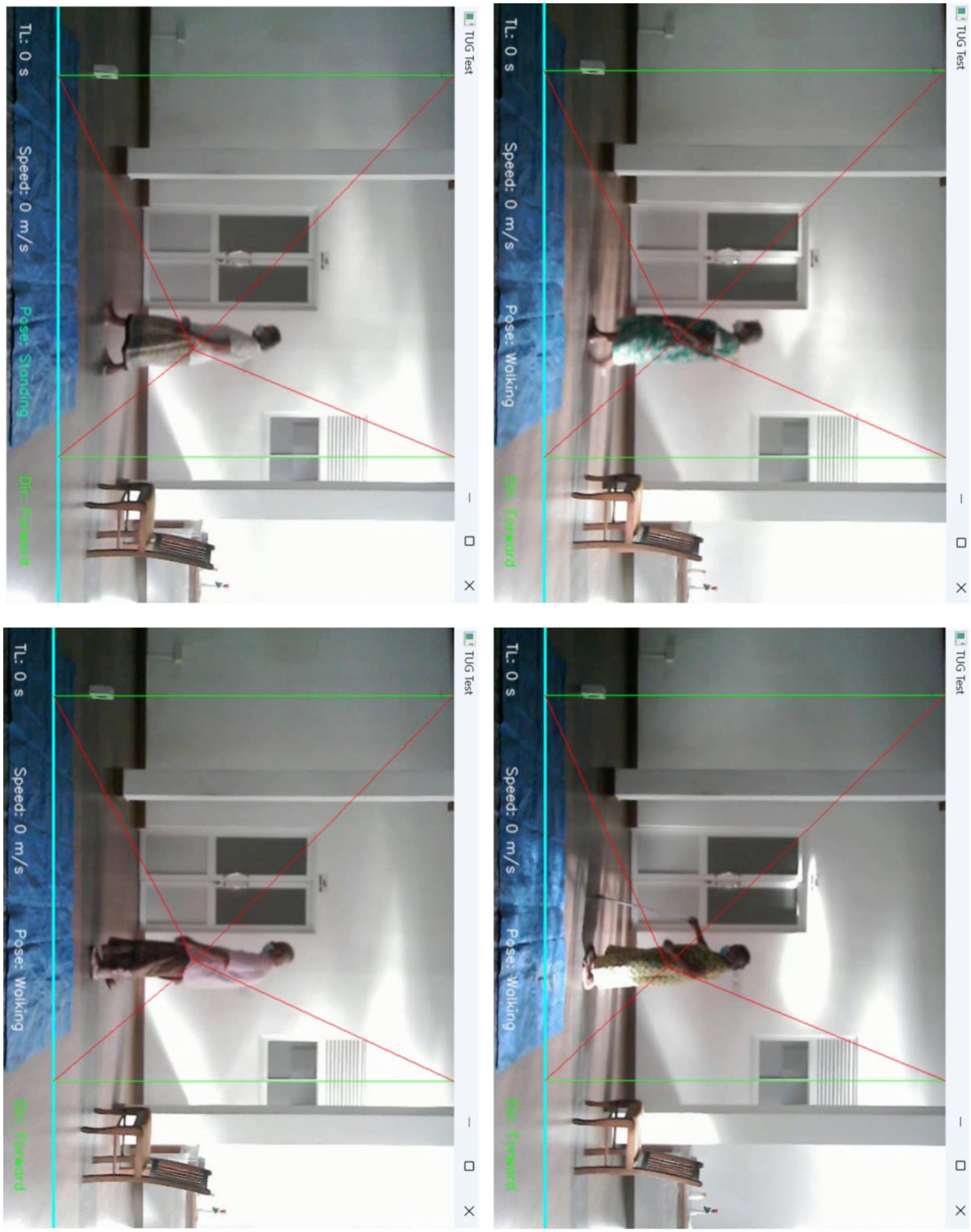
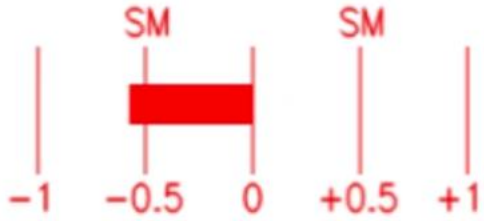


Fig. 5.2: TUG time and gait speed estimation during the experiment

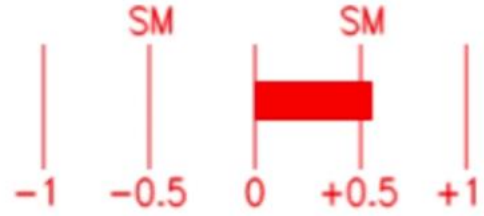
Figure 5.3 shows the test case experimenting on the fall score test to estimate the stability margin. As shown in the image, when a person performs the TUG test, the Graph shows the -1 to+1 range. Figure 5.4 shows the different stability margins for several test trials. As can be seen from the figure, negative values indicate a propensity for patients to lean left, while positive values indicate a tendency to lean right. It is imperative to acknowledge that the validity of this inference is contingent upon the

stability margin (SM) surpassing 0.5. On the other hand, SM values less than 0.5 suggest that although the patient may not have a fall risk score at this moment, one may eventually arise.

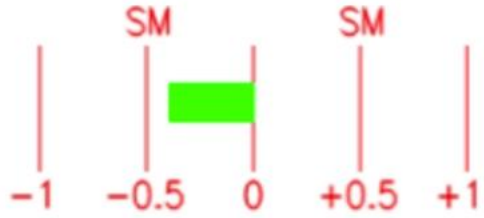
Fig. 5.3: Stability margin (SM) estimation during the experiment



Higher Fall Score (Tend to fall on left side)



Higher Fall Score (Tend to fall on right side)



Low Fall Score

Fig. 5.4: Different stability margin criterions

The analytical dashboard created using Python is seen in Figure 5.5. Eight graphs were designed to evaluate the functional mobility of the elderly, as the photos demonstrate. A graph illustrating distance fluctuation with TUG time is presented. We can determine whether the patient completed the TUG test by using this. The patient's hip and knee angles showed whether or not their aberrant gait pattern was causing them difficulty walking. When a patient has an irregular gait, back discomfort is likely the cause. Additionally, the TUG test reveals the patient's changing gait through the forward and backward speed variations. We can lessen the inaccuracy in gait speed by averaging the values. The stability margin indicates whether the patient is stable throughout the examination. These instabilities were mapped with notable grip strength, which measures an individual's muscular strength.

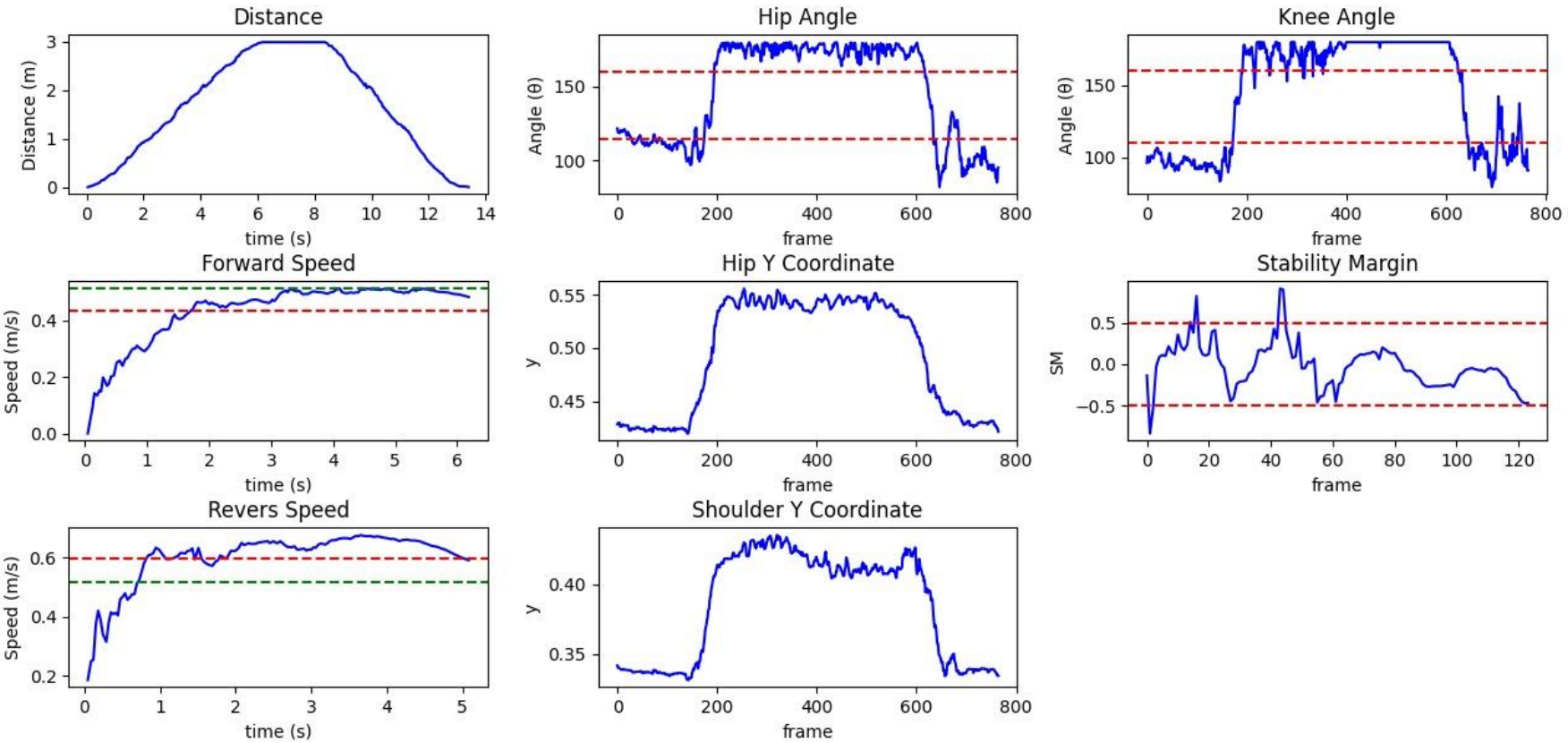


Fig. 5.5: Functional mobility analysis dashboard (Top: a: Distance variation graph, b: Hip angle variation graph, c: Knee angle variation, Middle: a: Forward speed variation, b: Hip *y*-coordinate variation, c: Stability margin variation, Bottom: a: Reverse speed variation, b: Shoulder *y*-coordinate variation)

The proposed sarcopenia screening tool's functional mobility analysis dashboard is shown in Figure 5.4. The distance graph, as seen in the figure, demonstrates how the distance varied throughout the TUG test. If someone follows the proper instructions and does a TUG test, the shape must resemble the one in the figure. The average gait speed was determined by averaging the forward and reverse 3m walks. The critical values are displayed in the redline margin. A person cannot walk at a healthy speed if the continuous speed is below the red line. The functional acceptability of the TUG test was assessed by hip and knee angle variation. The 3m walk range needs to remain consistent during the TUG test. If the variance is more significant, the person cannot do the sit-to-stand, stand-to-sit, and 180-degree TUG activities. The caretaker in this situation must be cautious of the patient since they could require gait help. To determine if a person has the proper body posture, the hip angle and shoulder *y*-coordinate are employed. *y*-coordinates cannot fluctuate at a high phase for the appropriate body position. The stability margin about the fall score finally represents the muscular strength.

5.2. Experiment Method and Data Collection

This experiment aims to evaluate the functional mobility and performance of sarcopenia patients during the TUG test. To achieve this, we will design a randomized controlled trial with two groups: an experimental group and a control group. To evaluate functional mobility, we collected TUG time, Gait Speed (using 3mW-T), and fall score.

Participants:

We recruited 348 participants (218 in the experimental group and 116 in the control group) from the local community. The inclusion criteria for this study are as follows:

- Participants must be 60 years or older
- Participants must be able to walk independently with or without the aid of an assistive device (e.g., cane, walker)
- Participants must be able to follow instructions and perform the TUG test

Procedure:

- Pre-test Assessment: Before experimenting, each participant will be assessed for their baseline mobility and cognitive function using a standardized assessment tool.
- Experimental Group: Participants in the experimental group will perform the TUG test using the computerized system. The system will consist of a motion sensor attached to the subject's waist to detect movement and time their performance automatically. Additionally, a video recording of the TUG test will be taken for later analysis.

- Control Group: Participants in the control group will perform the TUG test using a stopwatch to measure their performance manually. Additionally, a video recording of the TUG test will be taken for later analysis.
- TUG Test: Participants in both groups will be directed to don their usual footwear and utilize any customary gait aids employed during ambulation, while refraining from seeking assistance from another individual. Upon the instructor's prompt of "GO," subjects will commence the experiment, navigating through the tasks at a pace that aligns with their perceived sense of safety and comfort. The ensuing sequence of activities will unfold as follows:
    1. Initiate the experiment by rising from the chair, with the option for the subject to utilize the support of the chair arms if needed.
    2. Traverse a 3-meter (10 feet) distance, marked by masking tape indicating the destination.
    3. Execute a precise 180-degree turn upon reaching the designated destination.
    4. Retrace the 3-meter path back to the initial starting point.
    5. Perform another 180-degree turn upon returning to the starting location, allowing the subject to use the chair arms for support if necessary.
    6. Finish the sequence by smoothly and safely sitting back down in the chair.

Throughout the aforementioned sequence of activities, meticulous time measurements will be conducted. Specifically, we will calculate T1 for Activity 1, T2 for Activities 2, 3, 4, and 5 collectively, and T3 for Activity 6. These time calculations will be executed using both the computerized system and a traditional stopwatch, ensuring comprehensive and accurate data collection.

- Post-Test Assessment: After completing the TUG test, participants will be assessed for their mobility and cognitive function using the same standardized assessment tool as the pre-test.
- Data Analysis: The data collected from the TUG test will be analyzed to compare the performance of the experimental group and the control group. We will use the following statistical methods:

The proposed experimental configuration for the sarcopenia screening approach is shown in Figure 2. Two cameras, as seen in the image, were mounted to obtain video feeds of both the front and sagittal views. The sagittal camera is 4 m from the TUG arena's midpoint, with the camera set to 2 m from the destination. The 3m TUG arena served as the site of the TUG experiment.

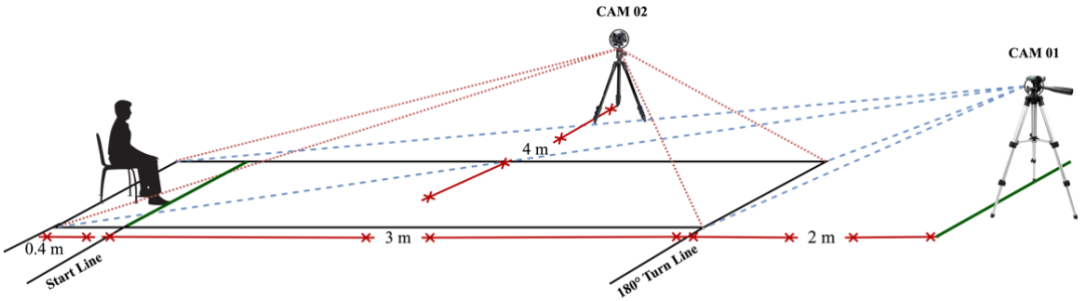


Fig. 5.6: Domestic sarcopenia screening vision-attentive experimental setup

Data labelling: After the data collection process was over, we classified all of the collected data thoroughly, making a distinction between the cases that showed signs of sarcopenia and the cases that showed signs of healthy (non-sarcopenia). Based on their medical histories, the records of 130 test cases revealed that the participants were experiencing problems with functional mobility. We used a number of criteria, such as the TUG time (>13 s) and conventionally measured gait speed, (1 ms^{-1}), together with prominent grip strength levels for males (<27 kg) and females (<16 kg), to demonstrate the presence of sarcopenia.

When we found cases in which the grip strength levels matched the defined thresholds for sarcopenia, we labelled them as “sarcopenia” cases. On the other hand, those with better grip strength ratings and strong functional mobility were considered to be “healthy” subjects. In order to verify the precision of our categorization, a medical officer reviewed the complete dataset, leading to the removal of fourteen records pertaining to test cases with unrecorded medical history, and abnormal functional mobility behaviors (further clinical testing required to consider for dataset). For the ensuing experimental analysis, the control group consisted of the remaining 116 data points.

5.3. Sarcopenia Prediction Through ANN Model

Researchers frequently utilise the t-test, a statistical analysis technique that examines the statistical significance of observed differences, in their search to identify significant variations between the means of two groups or samples. When comparing the means of two groups, researchers can apply this test to see if an observed difference is likely the result of a natural effect or if it might have happened by chance. Table 5.1 shows the independent sample *t*-test of the collected data. Age, Gender, Height, Weight, TUG Time, Gait Speed, and Fall Score all had *p*-values that were below the crucial cut-off of 0.05 in our comprehensive statistical study. This persuasive data suggests that these characteristics and the existence of Sarcopenia are related in a statistically meaningful way. These results highlight how crucial these factors are for comprehending and forecasting Sarcopenia outcomes.

However, when we looked at BMI, its corresponding *p*-value was 0.227, exceeding the 0.05 cut-off. This particular outcome suggests that the available data do not support

the claim that there is a strong relationship between BMI and sarcopenia. Given this result, it was wise to decide against using BMI as an input variable in our Artificial Neural Network (ANN) model because, according to our dataset, it makes little difference in predicting sarcopenia.

TABLE 5.1: INDEPENDENT SAMPLE T-TEST OF DATASET

Variables	*p*-value
Age	0.002 (<0.05)
Gender	0.006 (<0.05)
Height	0.002 (<0.05)
Weight	0.001 (<0.05)
BMI	0.227 (>0.05)
TUG time	0.001 (<0.05)
Gait speed	0.015 (<0.05)
Fall score	0.003 (<0.05)

Figure 5.7 shows the proposed ANN model to predict sarcopenia.

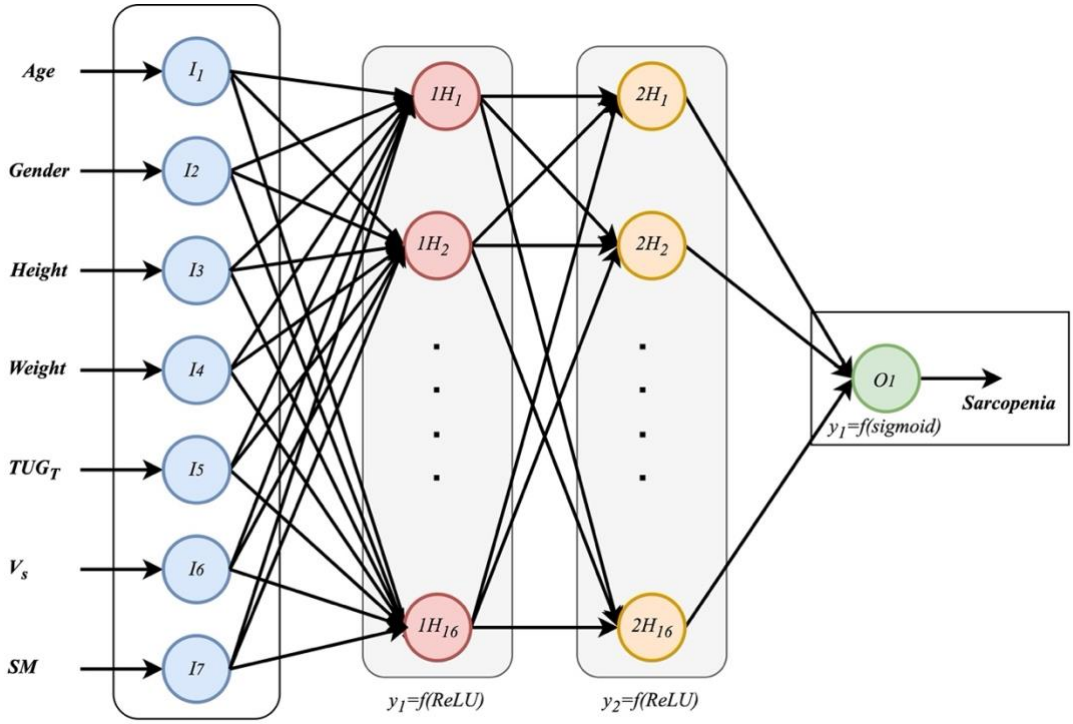


Fig. 5.7: Proposed sarcopenia prediction ANN model

We developed an exact system with Python, OpenCV, and MediaPipe library using the mathematical model above. We then used an ANN to determine if the test individual had sarcopenia after obtaining the TUG time, gait speed, and hip and knee angle data. A total of 165 data were collected, of which 80% were used to train the system and 20% to test it. Each ANN node was activated using a Sigmoid activation function ($f(x) = 1/(1 + e^{-x})$). Age, gender, TUG time, and gait speed were employed as the ANN's input features; if the output value (O_i) is less than 0.5 (O_i<0.50),

sarcopenia is considered to be less prevalent. If the output value (Oi) is more than or equal to 0.5 ($O_i \geq 0.50$), sarcopenia is deemed to be more prevalent. Severe sarcopenia was recorded in those with greater O_i values than 0.75 ($O_i \geq 0.75$).

5.3.1. Results and Discussion

In this section, we examine in extensive detail the results and analysis obtained from the Artificial Neural Network (ANN) model. Figure 5.8 shows the model loss and model accuracy of the ANN model. The ANN model evaluation produced encouraging results, as evidenced by a test accuracy of 90.91% and a test loss 0.21. These metrics highlight the model's promise as a dependable tool for classification and predictive analytics jobs by demonstrating its strong performance and capacity to generalize to previously unknown data.

A test loss of 0.21 indicates a significant convergence toward ideal parameter choices, indicating that the model can minimize mistakes during the validation process. The model's ability to effectively identify the underlying patterns in the dataset is demonstrated by the low loss value, which facilitates the generation of more precise forecasts and well-informed decisions.

Moreover, the impressive test accuracy of 90.91% supports the model's ability to classify data points accurately, indicating that it can recognize and distinguish between distinct data points with a high degree of accuracy. This degree of precision is necessary to guarantee that the model may successfully generalize to real-world situations, increasing its relevance and practical use across various areas.

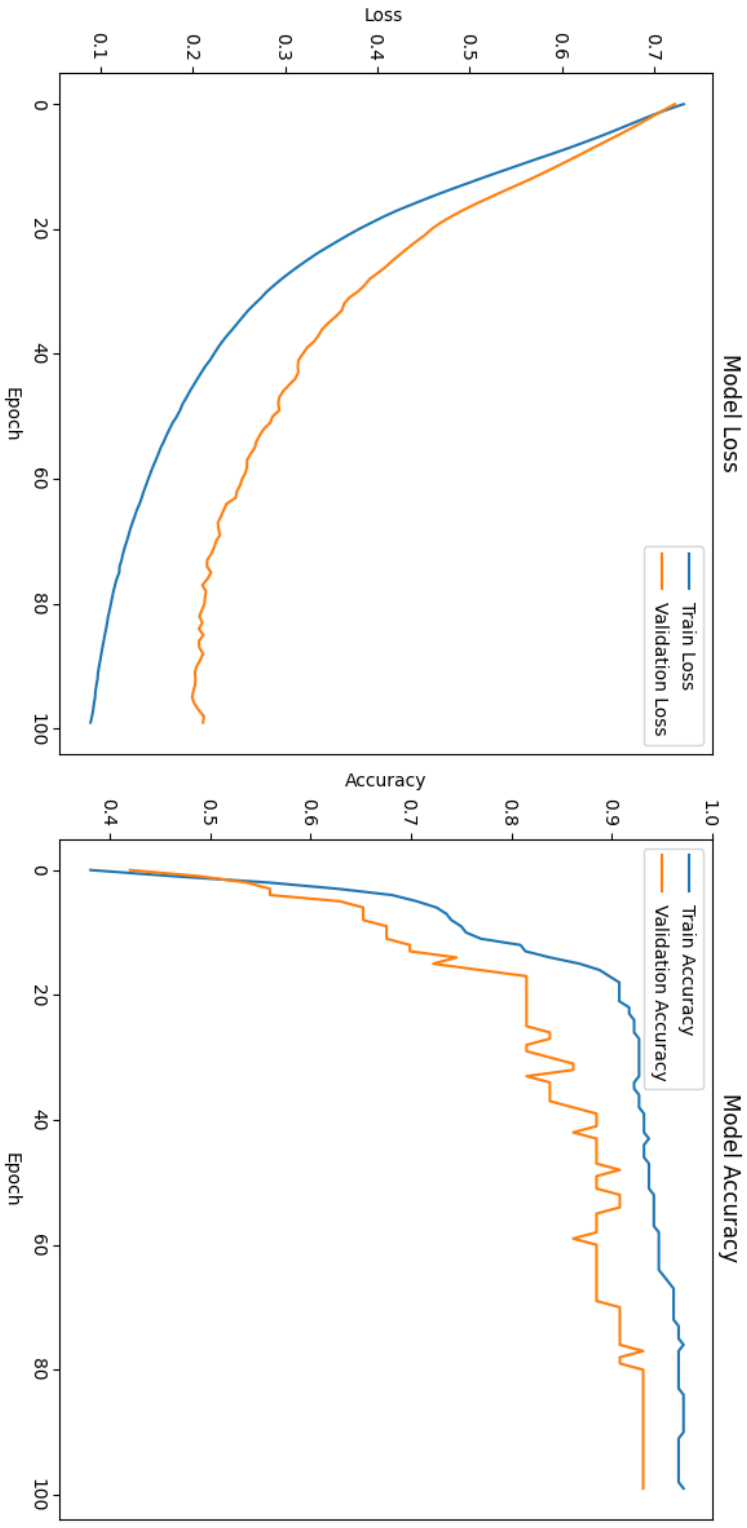


Fig. 5.8: ANN training, validation, and accuracy curves

In the study of machine learning and classification, a confusion matrix is a crucial tool. It is employed to gauge a prediction model's effectiveness, notably in binary classification jobs. The matrix offers a concise and unambiguous overview of how well a model's forecasts match actual results. True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN) are the four main categories that

make up this framework. Figure 5.9 shows the confusion matrix of the ANN prediction. The findings from the confusion matrix, together with a Test Loss of 0.21 and an outstanding Test Accuracy of 90.91%, show the model's strong performance in correctly categorizing data points. This high degree of accuracy indicates that the model's predictions and the actual results in the test dataset are quite similar. The Test Loss of 0.21 suggests that the model's predictions are not only consistently correct with little error but also accurate overall. These outcomes demonstrate the model's dependability and efficiency in its categorization tasks.

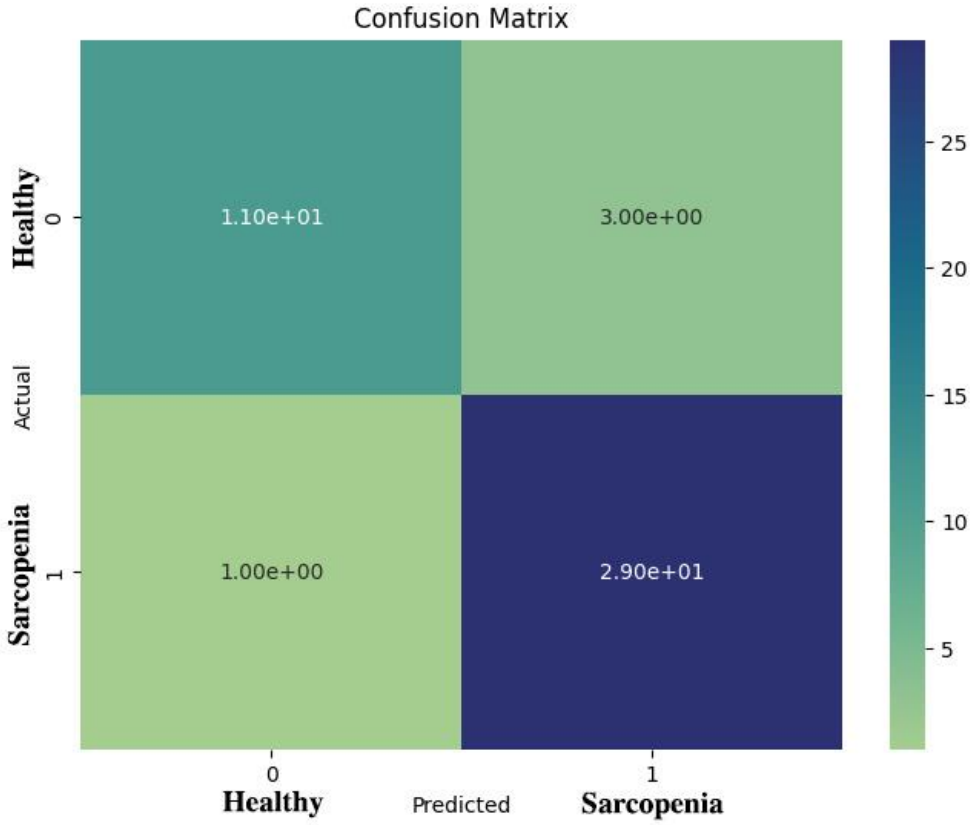


Fig. 5.9: Confusion matrix of the ANN prediction

Figure 5.10 shows the Receiver Operating Characteristic (ROC) of the experiment results. The performance of our model demonstrated an astounding 93.9% accuracy, according to the ROC curve study. When we looked more closely at the statistics, we saw that the calculations for sensitivity and specificity produced excellent outcomes, with sensitivity clocking in at 88.9% and specificity climbing to 97.1%. In-depth ROC analysis revealed that the fitted ROC region had a fantastic accuracy rate of 98.1%, highlighting the strength of our model's predictive skills. Notably, the empiric ROC area retained a high degree of accuracy although being significantly lower at 97.6%, confirming the validity of our strategy in this crucial examination.

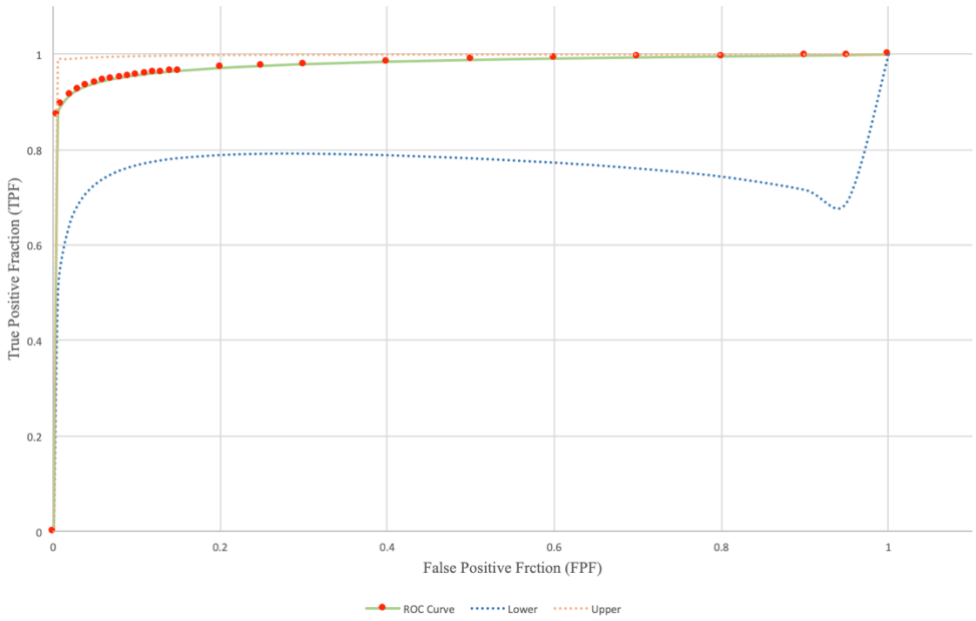


Fig. 5:10: ROC curve of the experiment

The most critical factors affecting sarcopenia status and their corresponding means are shown in Table 5.2. In the adverse scenario, when people do not have sarcopenia, the mean age is 62. In contrast, the mean age is much higher in sarcopenia-positive patients, at 76 years, indicating that sarcopenia tends to be more common in older people. Additionally, the average TUG test time is 12.37 seconds in negative instances as opposed to 23.07 seconds in positive ones, a substantial difference. Similar patterns can be seen in gait speed, assessed in meters per second (m/s), with negative instances showing a quicker average speed of 0.97 ms-1 compared to positive patients' slower 0.41 ms^{-1}. Additionally, grip strength in negative instances is 22.46 kg compared to the lower average of 8.57 kg reported in those with sarcopenia, which is a significant increase. These results show that people with and without sarcopenia significantly vary in these factors.

TABLE 5.2: VARIABLE MEANS FOR HEALTHY AND SARCOPENIA CASES

Variable	Sarcopenia Status	Mean Value
Age / (Yrs.)	Negative Case	62
	Positive Case	76
TUG Time (s)	Negative Case	12.37
	Positive Case	23.07
Gait Speed (ms^{-1})	Negative Case	0.97
	Positive Case	0.41
Prominent Grip Strength (kg)	Negative Case	22.46
	Positive Case	8.57

Figure 5.11 shows the TUG time variation between the proposed vision system and the clinical method. Compared to conventional stopwatch techniques, vision systems have been shown to produce Time Up and Go (TUG) time readings that are noticeably

more accurate. This significant increase in accuracy has the potential to completely change how we measure time for a variety of tasks, especially when it comes to evaluating mobility and functional performance. Furthermore, recent evaluations have shown the TUG system's total accuracy is 96.89%. This high degree of accuracy highlights the vision system's potential to be an essential tool in healthcare settings and other contexts, reaffirming its dependability and resilience.

The capacity of the vision system to remove mistakes resulting from human reading is one of its main features. The technology reduces the possibility of errors resulting from human interpretation while also streamlining the data-gathering process by precisely detecting and evaluating TUG operations. This is a significant advancement in improving the impartiality and dependability of our evaluations, which will eventually lead to better decision-making and individualized treatment for both patients and clients.

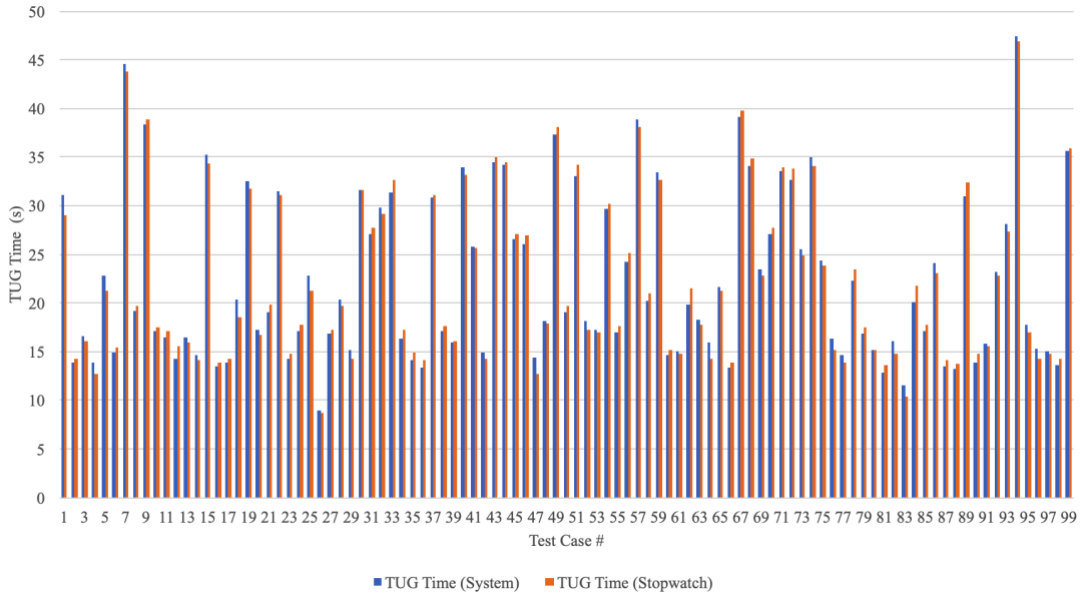


Fig. 5.11: TUG time comparison of vision system vs. clinical method

It is critical that we keep investigating the visual system's full capability in the future in order to our measuring methods and improve our comprehension of human movement and performance. By making use of this cutting-edge technology, we have the chance to uncover fresh viewpoints and insights that can spur innovation in the fields of healthcare and rehabilitation, thereby raising people's quality of life regardless of their background.

Figure 5.12 shows the gait speed variation between the proposed vision system and the clinical method. The proposed approach has demonstrated that the vision system's use has produced excellent results in assessing gait speed, with an astounding accuracy of 91.1%. This is a significant development in health monitoring technologies, especially for gait analysis. The methodology comprised the systematic evaluation of the mean walking speed, which was ascertained using the 3 m forward and backward walk segments of the Timed Up and Go (TUG) examination. We could guarantee

consistency and dependability in our measurements because of this standardized approach, which gave our study a firm basis. Furthermore, incorporating wearable sensor devices and smartphones has shown to be crucial in our data-collecting procedure. By utilizing these contemporary instruments, we managed to circumvent the constraints linked to traditional methods of gauging stride velocity. This improved the quality and precision of our results and expedited the data-collecting process, allowing us to get previously impossible levels of knowledge.

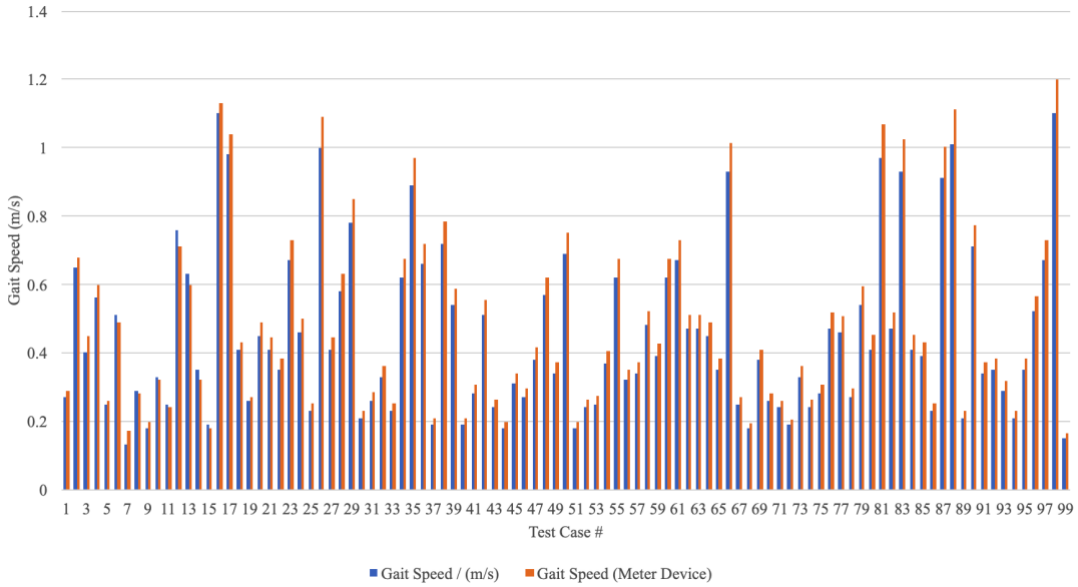


Fig. 5:12: Gait speed comparison of vision system vs. clinical method

CHAPTER 6

DISCUSSION AND CONCLUSION

Within the context of an aging demographic, the prevalence of sarcopenia emerges as a notable health concern, marked by the discernible decline in both muscle mass and functional capabilities. Effective intervention and management depend on early diagnosis and reliable screening technologies. For older people, traditional clinical exams for sarcopenia are less convenient and frequently require invasive procedures or specialized equipment. A viable alternative, however, is provided by a revolutionary strategy called the vision-attentive paradigm. The advantages of utilizing a vision-attentive model to assess functional mobility in a real-world household context as a more trustworthy screening tool for sarcopenia in older persons are explored in this debate. The vision-attentive paradigm uses inconspicuous cameras to document and assess the functional mobility of older people. This strategy may be applied in common living areas and is non-intrusive and affordable. The vision-attentive approach captures a more realistic portrayal of seniors' functional mobility, frequently impaired in sarcopenia, by watching their everyday activities within their homes. To adequately screen for sarcopenia, the WHO has acknowledged the necessity for numerous evaluations.

Sarcopenia, a disorder marked by the progressive loss of muscle mass and function, is becoming more and more of a global health problem, especially in older people. Although wearable sensor-based technologies have gained ground in health monitoring, extensive sarcopenia screening is challenging to deploy due to the aversion of many older people to such devices. As a result, the creation of a vision-attentive-based system, as described in this study, offers a significant improvement in locating people who are at risk and permitting early intervention techniques.

The TUG test, 3-meter Walk Test (3mW-T), and fall score model was all integrated into the vision-attentive system, which not only permits successful screening but also contributes to a thorough evaluation of functional mobility in older persons. The use of these criteria has shown a clear relationship between sarcopenia and age, TUG time, gait speed, fall score, and other variables. The dependability of the vision-attentive system in correctly diagnosing sarcopenia in old people is further supported by the statistical significance of these relationships, as shown by the *p*-values. Age, gender, height, weight, TUG time, gait speed, stability margin, and prominent grip strength were the many variables collected for this study. It is noteworthy that the stability margin is associated with grip strength, underscoring the need to evaluate functional mobility thoroughly. Artificial Neural Networks (ANNs) were used in the study to analyze the data and forecast sarcopenia. To make sure the most important aspects were taken into account, input variable selection was carried out using an independent sample test (*t*-test). The ANN's outstanding accuracy rate of 90.91% demonstrated how effective a prediction tool it is. The vision-attentive model's promise as a trustworthy sarcopenia screening tool was further supported by Receiver Operating Characteristic

(ROC) analysis, which showed that the proposed method had an astounding 93.9% accuracy.

The primary benefit of the vision-attentive system is that it is non-invasive, which increases older people's acceptance of it. The technology enables early sarcopenia identification without intrusive technologies by utilizing visual clues and easy mobility tests, encouraging a more patient-friendly approach to treatment. Furthermore, the system's excellent accuracy rates demonstrate its dependability and efficiency in detecting at-risk people, enabling prompt intervention and customized care programs.

Several restrictions must be taken into account, however. The emphasis may impact the screening process's consistency and objectivity on visual evaluation, which might add subjectivity and unpredictability. Furthermore, the system's application in real-world settings, where environmental conditions might fluctuate, may be constrained by the requirement for a controlled environment for precise vision-based analysis. Additionally, the lack of a standardized technique for performing the TUG and 3mW tests may compromise the repeatability of findings in various healthcare environments.

Despite this, the research opens up new possibilities for investigation and progress in geriatric care. The combination of machine learning and artificial intelligence algorithms may be one of the research avenues taken in the future to improve the accuracy and dependability of the vision-attentive system. By using these technologies, it is possible to create predictive models that might be used to predict future functional decline and fall in older persons and diagnose sarcopenia. A more thorough assessment of sarcopenia could also be possible with the addition of further variables like muscular strength and body composition analyses. Clinicians can better comprehend a patient's musculoskeletal health by including these characteristics in the current vision-attentive system, which will make it easier to conduct focused and specialized therapies.

Future research should standardize the evaluation methodologies and build a thorough validation process for the vision-attentive system across various groups to solve the existing shortcomings. Demonstrating its dependability and efficacy in multiple clinical contexts would encourage its wider acceptance and inclusion into standard geriatric care.

In conclusion, creating a vision-attentive system for sarcopenia screening marks a significant advancement in the early recognition and treatment of this debilitating condition among the elderly. Although the system has several drawbacks, such as possible subjectivity and environmental limits, its non-invasive design and high accuracy rates make it a viable tool for enhancing older people's healthcare results and quality of life.

The integration of cutting-edge technology and the extension of evaluation criteria will be crucial in improving the vision-attentive system and expanding its usefulness in many healthcare settings as we look to the future. This method can potentially revolutionize geriatric care by resolving the present constraints and adopting a more

thorough approach, permitting proactive treatments and promoting healthy aging internationally.

ETHICAL CONSIDERATION

This research granted ethical clearance approval from the University Ethics Review Committee (UERC) of the University of Moratuwa, Sri Lanka under the ethics declaration number ***ERN/2023/013***.

LIST OF PUBLICATIONS

[1]. Herath, H. M. K. K. M. B., Jayasekara, A. G. B. P., Madhusanka, B. G. D. A., & Karunasena, G. M. K. B. (2023). Attentive Vision-Based Model for Sarcopenia Screening by Automating Timed Up-and-Go (TUG) Test. In Enabling Person-Centric Healthcare Using Ambient Assistive Technology, Springer, pp. 85–103, Jan. 2023, doi: https://doi.org/10.1007/978-3-031-38281-9_4.

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[4]. H. M. K. K. M. B. Herath, A. G. B. P. Jayasekara, and B. G. D. A. Madhusanka, and G.M.K.B. Karunasena, “Non-Invasive Tools for Early Detection and Monitoring of Sarcopenia in Older Individuals,” in Moratuwa Engineering Research Conference 2023 (MERCon) *(Presented)*, 2023.

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APPENDIX A

CONSENT FORM

Research Title: Vision Attentive Model for Early Recognition of Sarcopenia with Limited Mobility of Elders in Domestic Environments

Prof. A.G.B.P. Jayasekara

Dr. B.G.D.A. Madhusanka

Ethics Declaration Number: ERN/2023/013

Consent by the participant

I have read and understood the **Information Statement** and the **Consent Form**, and any questions I have been asked, have been answered to my satisfaction. I agree voluntary participation in the study described in the Information Statement, realizing that I may withdraw at any time.

I agree that research data provided by me or with my permission during the study may be published in theses, conferences and in journals on the condition that anonymity is preserved and that I cannot be identified.

Name of Participant : …….

Signature : …….

Date : …….

Statement by the researcher/person taking consent

I have accurately read out the information sheet to the potential participant, and to the best of my ability made sure that the participant understands the research procedure. I confirm that the participant was given an opportunity to ask questions about the study, and all the questions asked by the participant have been answered correctly and to the best of my ability. I confirm that the individual has not been coerced into giving consent, and the consent has been given freely and voluntarily.

Name of Researcher : …….

Signature : …….

Date : …….

APPENDIX B

EVALUATION FORM

Research Title: Vision Attentive Model for Early Recognition of Sarcopenia with Limited Mobility of Elders in Domestic Environments

Experiment #: ……. Date: ……

Test Case #: …….

Age (Yrs.)	:		
Gender	:	Male ◯ Female ◯	
Weight (kg)	:		
Height (cm)	:		
BMI	:		
Grip Strength Measurements			
Left Grip Strength (kg)	:		
Right Grip Strength (kg)	:		
Prominent Grip Strength (kg)	:		
Experiment Readings			
Methodology		**Proposed System**	**Conventional Method**
TUG Time (s)	:		
Gait Speed (m/s)	:		
Fall Score (Stability Margin)	:		
Sarcopenia Status			
Sarcopenia Score	:		

Name and Signature of the Instructor: ……

Date: ……

APPENDIX C

SAMPLE DATASET

TABLE A1: SAMPLE DATASET COLLECTED

Gender (Female 0, Male 1)	Age/(Yrs.)	Height/(cm)	Weight/(kg)	Prominent GS/(kg)	TUG Time/(s) (System)	TUG Time/(s) (Stopwatch)	Gait Speed/(m/s)	SM
1	95	135.5	33.1	8	31.1	29	0.27	0.46
1	67	149.6	43.7	12	13.9	14.3	0.65	0.5
1	74	149.7	54.1	2	16.6	16.1	0.4	0.35
1	75	143.5	45.5	10	13.9	12.7	0.56	0.36
1	60	160.8	69.3	4	22.8	21.2	0.25	0.43
1	80	132	33	8	14.9	15.4	0.51	0.31
0	75	162.5	46.9	16	44.5	43.82	0.13	0.42
1	72	137.6	48.5	2	19.2	19.75	0.29	0.33
1	92	138.5	32.2	5	38.3	38.8	0.18	0.51
0	80	158.5	52.2	15	17.1	17.45	0.33	0.41
0	80	147	39.9	9	16.4	17.17	0.25	0.4
0	63	152.5	47.2	18	14.2	15.6	0.76	0.31
0	72	154.3	45.3	18	16.4	15.92	0.63	0.34
1	72	132.8	52.6	5	14.7	14.16	0.35	0.39
0	82	150.5	45	2	35.2	34.32	0.19	0.55
0	63	164.6	65.8	25	13.5	13.9	1.1	0.27

0	81	161	61.6	25	13.9	14.3	0.98	0.21
1	77	140	42	4	20.3	18.55	0.41	0.53
1	80	140.7	34.2	2	32.5	31.69	0.26	0.67
0	76	160.3	52.2	15	17.2	16.78	0.45	0.49
1	76	144.6	32.2	4	19.1	19.88	0.41	0.42
1	78	143	42.9	11	31.48	31.03	0.35	0.49
0	60	159.7	51.3	12	14.2	14.76	0.67	0.51
1	66	141.5	54.9	7	17.1	17.8	0.46	0.35
1	65	146.6	57.5	8	22.8	21.2	0.23	0.62
1	60	148.2	90.2	21	8.9	8.67	1	0.2
1	75	137.2	39.4	10	16.8	17.2	0.41	0.39
0	75	140.1	38.2	2	20.4	19.67	0.58	0.69
0	60	156.1	57.1	18	15.2	14.26	0.78	0.37
1	79	137.8	54	4	31.6	31.56	0.21	0.63
1	84	139.4	57.4	5	27.1	27.78	0.26	0.59
0	93	151.2	40	5	29.8	29.13	0.33	0.61
1	60	140	40	2	31.3	32.7	0.23	0.54
0	76	156.5	49	18	16.3	17.2	0.62	0.27
1	69	145.7	53.5	15	14.1	14.9	0.89	0.28
0	68	168	60.1	17	13.3	14.12	0.66	0.29
1	80	137.6	32.3	0	30.8	31.1	0.19	0.66
0	80	155.9	47.3	21	17.1	17.6	0.72	0.3
0	65	164	48.2	16	15.9	16.1	0.54	0.35
1	80	138	32.3	0	34	33.2	0.19	0.8
1	73	132.9	58.4	10	25.8	25.63	0.28	0.46

1	62	145.5	45	7	14.9	14.3	0.51	0.38
1	85	139	55.8	2	34.5	34.96	0.24	0.44
1	84	143.5	36.6	7	14.8	34.46	0.18	0.5
1	82	151.6	59.3	8	17.8	27.12	0.31	0.56
1	69	147.1	58.5	4	26.1	26.9	0.27	0.53
1	65	144.2	37.7	8	14.4	12.7	0.38	0.28
1	82	147.2	40.4	7	18.2	17.86	0.57	0.38
1	74	147.3	46.9	8	37.3	38.07	0.34	0.56
1	80	142.8	39.9	7	19.1	19.7	0.69	0.31