Ariel University

Master's thesis research proposal

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Identifying gait patterns using deep learning algorithms

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1. Introduction

Falls attributable to balance disorders are a major public health problem worldwide and are not just a problem of advanced age. Rates of fall-related injuries in the general population are substantial regardless of population ageing, indicating a failure of intervention strategies and the need for new approaches to fall prevention. Cohort-based population studies show that the estimated annual prevalence of falls triples from 9% among 40- to 44-year-old adults to 28% among 60- to 64-year-old adults (Peeters et al. 2018, Peeters et al. 2019), suggesting that middle age may be a critical life stage for preventive interventions.

Studies have shown that measures of physical performance in midlife can be used to develop clinical predictive models of disability later in life (Dodds et al., 2018). Human gait can also be used for age estimation, such application is of great interest and significance (Lu and Tan, 2010). For example, it may be used to identify individuals with gait profiles that do not fit their chronological age. Therefore, simple tools for the quantitative assessment of gait are needed to early detect the onset of changes in gait patterns.

There are several research approaches on how to estimate the chronological age of subjects. Some researchers such as the study by Aderinola et al. (2021) identify a subject's age with vision-based approaches and use image processing techniques to extract features from images or videos, and use deep learning algorithms to classify the subject's age. In another study, Chen et al. (2021) developed contactless and non-intrusive gait-based age estimation system, which leverages wireless sensing to perform gait analysis to infer the age of individuals. The disadvantages of these approaches are that you need special equipment or that the differences between the photographs obtained - the type of device, the angle, the lighting can affect the prediction results.

Gait analysis based on inertial measurement units (IMU), such as accelerometers and gyroscopes, is widely used to assess movement during aging. The increasing popularity of this method may be related to the availability and lower cost of these sensors, which are built into all modern smartphones (Shahar and Agmon, 2021). For example, in a recent study, the Physics Toolbox application was used to capture smartphone sensor signals and analyze gait patterns (Garcia-Barrientos et al., 2022).

In the last two decades, studies have used gait features for age estimation using various machine learning algorithms such as Random Forests (RF), Support Vector Machine (SVM), and Deep Convolusion Neural Networks (DCNN) (Ahad et al., 2020). Riaz et al. (Riaz et al., 2019) reported a root-mean-square error (RMSE) of 3.32 years in estimating participants' ages, based on 6D acceleration and angular velocity data recorded by smartphone embedded IMUs and a dedicated wearable IMU. In another study by Pyrkov et al. (Pyrkov et al., 2018), DCNN was used to determine biological age based on a large dataset of physical activity of subjects recorded by a smartphone IMU. The three different prediction models in this work showed an RMSE between 14 and 16 years. In another recent study for the purpose of identifying a user's gender, the researchers use time series data obtained from the use of a smartphone that arrive in 1D and transform them by using the Continuous Wavelet Transform (CWT), a mathematical tool used to analyze the frequency content of signals into 2D. Using CWT allows the model to identify important features more and use a combination of CNN and LSTM models (Davarci and Anarim, 2023) or a combination of several different LSTM models into one network such as GRU and BiGRU (Tarekegn et al., 2023).

The previously mentioned studies relied on different experimental setups for data collection, but none of them were based on a single gait measurement recorded independently by the subject. Moreover, the data were collected when the sensors were precisely placed at a specific body location. To enhance the accessibility of age prediction based on walking data, it is imperative to formulate a model proficient in estimating age reliably, even when the sensors are positioned more flexibly rather than with strict precision.

.2. Research objectives and expected significance

The main goal of our research is to create a model that is able to identify a person's age group by analyzing their gait. The use of age classification through gait analysis can provide important insights into the subject's stability. Our motivation stems from the fact that in the case of correctly identifying a patient whose true age contradicts the classification based on stability, a therapist will be able to provide tailored treatment aimed at strengthening stability, thus preventing future falls at an advanced age.

Unlike the previous studies in which the measurement was done "under laboratory conditions" so that the mobile device was attached to the body in a meticulous manner, our study examines whether it is possible to predict the subject's age based on their gait when the mobile device is freely held in front of their chest without anything anchoring it. This makes the test more accessible to patients, allowing them to perform the assessment in the comfort of their own home.

During the study, we aim to ascertain the appropriate threshold for defining "middle age" concerning walking stability. Additionally, we will investigate potential gender disparities in defining middle age and discerning patterns of gait (is there a difference in the middle age threshold and is the level of accuracy based on the walking data different). An essential aspect of our inquiry involves evaluating the model's precision and potential sources of error. For example, an error of the model and the classification of a 42-year-old subject as over middle age is different from the classification of a young 30-year-old subject as over middle age, ensuring its reliability and applicability in diverse contexts.

3. Methodology

3.1 Participants

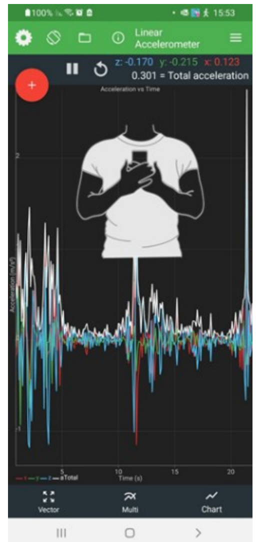
The goal of a proof-of-concept study with a clinical machine learning model is to estimate the performance metrics of the model. That is, to measure the accuracy of the model. Because medical machine learning models are complex, traditional statistical sample size calculations are less appropriate for this technique. Based on previous similar studies (Vabalas et al., 2019) the study will include a convenience sample of 150 young adults (18 – 45 years), 150 middle-aged adults (45-65 years), and 150 older adults (>65 years).

Participants will be enrolled if they are able to walk independently without an assistive device and have no limitations in physical activities of daily living and leisure time. Exclusion criteria include severe musculoskeletal, neurological, or visual impairments or other conditions that may affect mobility and balance. Participants will be recruited through public advertisements in the community and social media. All participants will provide written informed consent prior data collection. In addition, the participants will answer 4 questions examining the physical activity they performed during the last week (intense physical activity, moderate physical activity, walking and sitting)- IPAQ test. The questionnaire can be found in the Appendix.

3.2 Data collection

Acceleration gait data will be collected using Physics Toolbox, a free smartphone application by Vieyra Software (https://www.vieyrasoftware.net/). Data will be recorded during a single session of walking in a straight line for 30 seconds while the subjects hold the smartphone in front of their chest, as shown in *Figure 1*. In order to produce uniformity among the data, the measurements will be performed on the laboratory's mobile device and not on the subjects' personal device.

Figure 1: An illustrative depiction captured from the Physics Toolbox Accelerometry depicting how the subject should hold his smartphone during the session.



Participant personal information (phone number, age, gender, height, weight), responses pertaining to physical activity status, (briefBESTest and IPAQ - explanation in the paragraph below) and accelerometer-generated data are gathered utilizing the Qualtrics software in which the laboratory personnel enter the data. Subsequently, these datasets are exported to CSV files, we will use Python to analyze the data and build a model.

At the same time as conducting the mobile phone experiment, upon arriving at the laboratory, the experimenters answer a system evaluation balance test known as briefBESTest. This test has been carefully designed to identify potential balance problems and distinguish the underlying systems that contribute to any balance impairment. Its discriminating ability extends to identifying people aged 50 and over who are at high or low risk for falls (O'Hoski et al., 2015), while providing age-normative scores (O'Hoski et al., 2014). Another test that the subjects answer is the IPAQ. IPAQ stands for International Physical Activity Questionnaire. It is a widely used tool for assessing levels and patterns of physical activity in adults. The IPAQ asks people about the frequency, duration, and intensity of various types of physical activity, including walking, moderate-intensity activities, and vigorous-intensity activities, over a specified period of time. The questionnaire is in the appendix. Through the application of briefBESTest and IPAQ, our goal is to examine whether any observed discrepancies in model results are due to prediction errors or whether there is a medical rationale for these discrepancies.

3.3 Data analysis and Machine Learning methods

The research - focuses on the development of a model that accurately classifies individuals into age groups based on their gait data, while distinguishing between 2 age groups - below middle age and above middle age (the cut-off age will be determined according to the results of the study). The classification process will employ both classical machine learning algorithms and deep learning methods. Given the limited volume of available data and the aspiration to enhance the model's generalizability, the k-fold cross-validation technique will be employed.

In assessing the model's performance, an array of metrics will be computed, including Recall, Precision, Accuracy, AUC-ROC, and Brier's Score. These metrics collectively offer a comprehensive evaluation of the model's predictive prowess and its ability to discern age groups based on gait data.

3.3.3 Classical machine learning

Manual feature extraction will include features of the trunk acceleration signal such as: Mean, standard deviation (SD), Median, inter-quartile range (IQR), kurtosis, skewness, range, minimum, maximum, number of peaks, average distance between peaks, the derivative of the signal or the Fourier transformed signal. The extracted features are used to train logistic/multinomial regressions or tree-based models (XGBoost, LightGBM).

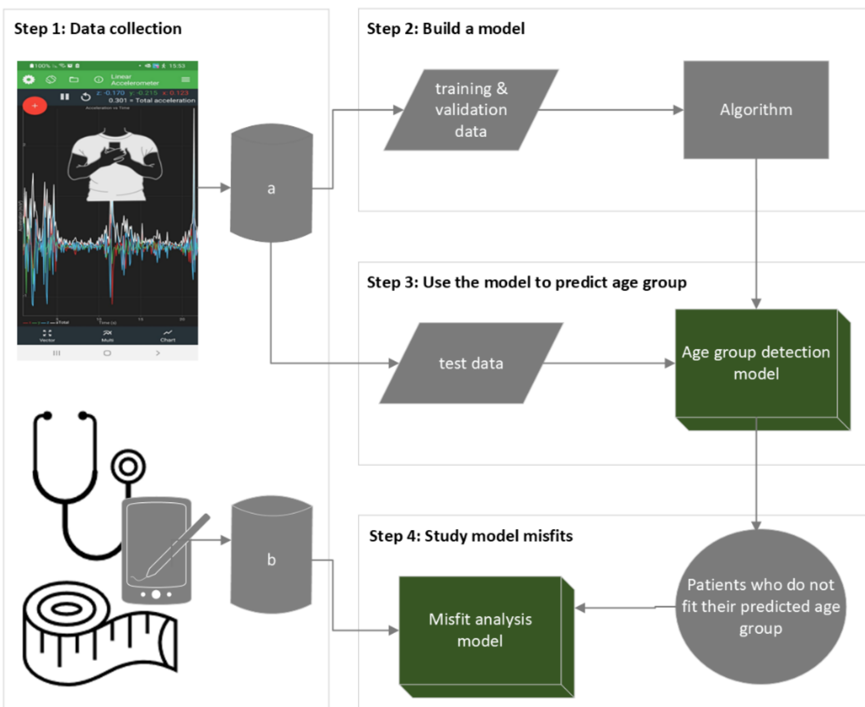
3.3.4 Deep learning

Pre-processing for the deep learning model will include none (raw signal), filtered signal, Fourier transformed signal or Continuous Wavelet Transformed signal. We will train 1D or 2D convolution neural networks to automatically learn features from the pre-processed data.

3.3.5 Further analysis to validate the model

The mobile phone-derived gait data is divided into two arrays: "train and validation data" and "test data". Following this, we train the model with the training set (using deep learning algorithms), with the objective of predicting the subject's age group in the distinct test data set. In instances where the model's age group predictions diverge from the observed outcomes, subjects undergo an additional assessment probing their stability status, meticulously evaluated through the succinct briefBESTest. This dual evaluation is designed to ascertain whether the model's predictions were erroneous or if they astutely identified incongruities between the subject's postural condition and chronological age group. In the final stage we will consider and check how many cases the model predicted accurately and in how many cases the model results were wrong.

Figure 2*: A visual representation delineating the conceptual framework of the project.*



3.4 Preliminary Results

Before I (Itzhak) joined the study, a pilot study was conducted by the research team (with the help of Uri Gottlieb who retired from the team. The pilot study included 172 subjects (95 women, age: 45.0±18.1). As described above, subjects were classified into two groups (up and over 45 years of age), based on their gait data. They used a 5-fold cross-validation (i.e., a resampling method that uses different portions of the data to train and test a model on different iterations) and obtained a AUC ROC-curve ranging from 0.671 to 0.835.

Upon joining the team, I constructed a questionnaire using Qualtrics survey platform. to the questionnaire collects the input of results from the briefTESt test and accelerometer data obtained during the walking test by both laboratory personnel and participants. The collected data can be downloadable in CSV files. In addition, an I examined the current (simple) algorithm before beginning to improve the algorithm.

4. Work plan and schedules

	subject	**Start date**	**End date**
1.	Build a protocol for data- collection	15/09/23	15/10/23
2.	Conducting the experiment for subjects	01/01/24	30/03/24
3.	Build the model using data obtained from the initial study	01/01/24	30/03/24
4.	Data processing, extraction of anomalous data, model experimentation on the received data and refinement of the model	01/04/24	30/05/24
5.	Check the results, summarize the results and write the thesis	01/06/24	30/07/24

**Due to the war and my reserve service and the reserve service of part of the research team that is responsible for conducting the experiment for the experimenters, there may be changes in the rate of progress of the research.*

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Appendix

The IPAQ (International Physical Activity Questionnaire):

שאלון פעילות גופנית

אנו מעוניינים לבחון את סוגי הפעילות הגופנית שאנשים מבצעים כחלק מחיי היום יום. השאלות הבאות מתייחסות להרגלי הפעילות הגופנית שלך **ב- 7 הימים האחרונים.** אנא השב/י לכל תשובה גם אם אינך מגדיר/ה את עצמך כאדם פעיל גופנית. חשוב/חשבי על פעילות שהינך מבצע/ת בזמן העבודה, כחלק ממטלות הבית והעבודה בגינה, כאמצעי תחבורה ממקום למקום, כפעילות בזמן הפנאי, וכפעילות גופנית וספורט.

1. חשוב/חשבי על כל הפעילויות **העצימות** שביצעת **ב 7- הימים האחרונים.** פעילות גופנית **עצימה** מתיחסת למאמץ קשה, הגורם לך להתנשף הרבה יותר במאמץ לעומת מנוחה. חשוב/חשבי רק על פעילות גופנית שביצעת לפחות 10 דקות בכל פעם.

א) במהלך **7 הימים האחרונים**, בכמה ימים ביצעת פעילות גופנית **עצימה,** כמו הרמה של משאות כבדים, חפירה, אירובי, רכיבה מהירה על אופניים?

_________ **(מספר ימים בשבוע)**

ב) במשך כמה זמן על פי רוב ביצעת פעילות גופנית **עצימה** באחד מימים אלה? ______ **שעות,** _______ **דקות.**

או סמן/י בריבוע אם לא מבצע/ת פעילות גופנית ☐

2. חשוב/חשבי על כל הפעילויות המתונות שביצעתם ב 7- הימים האחרונים. פעילות גופנית **מתונה** מתייחסת למאמץ בינוני, הגורם לך להתנשף יותר במאמץ לעומת מנוחה. חשוב/חשבי רק על פעילות גופנית שביצעת לפחות 10 דקות בכל פעם.

א) במהלך **7 הימים האחרונים**, בכמה ימים ביצעת פעילות גופנית **מתונה**, כמו הרמה של משאות קלים, רכיבה על אופניים בקצב רגיל או טניס זוגות? אל תכליל/י הליכה

_________ **(מספר ימים בשבוע)**

ב) במשך כמה זמן על פי רוב ביצעת פעילות גופנית מתונה באחד מימים אלה? ______ **שעות**, _______ **דקות.**

או סמן/י בריבוע אם לא מבצע/ת פעילות גופנית ☐

3. חשוב/חשבי על הזמן שהקדשת **להליכה** ב 7- הימים האחרונים. זה כולל במקום העבודה ובבית, **הליכה** לשם הגעה ממקום למקום וכן כל הליכה שהנך מבצע/ת לשם פנאי, פעילות גופנית או ספורט.

א) במהלך **7 הימים האחרונים**, בכמה ימים ביצעת **הליכה** לפחות למשך 10 דקות בכל פעם?

_________ **(מספר ימים בשבוע)**

ב) במשך כמה זמן על פי רוב ביצעת **הליכה** באחד מימים אלה? ________ **שעות**, ______ **דקות.**

או סמן/י בריבוע אם לא מבצע/ת פעילות גופנית ☐

השאלה האחרונה מתייחסת לזמן שהנך מבלה **בישיבה** במהלך השבוע ב 7- הימים האחרונים**.** כלול/י זמן שהנך יושב/ת בעבודה, בבית, בלימודים ובזמן הפנאי. ניתן לכלול זמן ישיבה ליד שולחן, ישיבה בבילוי אצל חברים, בזמן קריאה, או ישיבה או שכיבה כדי לצפות בטלוויזיה.

4. במשך 7 הימים האחרונים, כמה זמן הנך מבלה **בישיבה** במהלך יום חול (יום באמצע השבוע)?

________**שעות,** _______ **דקות.**

עד כאן השאלון. תודה על השתתפותך!