Opening the Personal Gate between Technology and Health Care
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Dementia Prediction Using Gait Analysis and Machine Learning

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Abstract. Dementia is a progressive neurodegenerative disorder affecting millions of people worldwide. Early prediction of dementia, especially during the mild cognitive impairment (MCI) stage, is crucial for timely intervention and management. Gait analysis provides indicators of cognitive decline and help identify individuals at risk of progression. This study aims to extract gait features from video recordings and apply machine learning models (Support Vector Machine (SVM), XGBoost, and Logistic Regression (LR)) to predict conversion from MCI to dementia. The dataset consists of videos from 62 individuals with MCI, of whom 31 later converted to dementia at 2-year follow-up. Participants performed the Timed Up and Go (TUG) test under single-task and dual-task (TUGdt) conditions, including animal naming (TUGdt-NA) and reciting months in reverse order (TUGdt-MB). The results showed that SVM achieved the highest performance with an accuracy of 70% and F1 score of 69%. These findings show that gait-based machine learning models, particularly SVM, show promise for early prediction of dementia conversion in individuals with MCI.

Keywords. Dementia, Mild Cognitive Impairment, MCI, Gait Analysis, Machine Learning, Pose estimation, prediction

1. Introduction

Dementia is a major global health challenge. Around 55.2 million people globally were living with dementia in 2019, and the number is projected to rise to 139 million by 2050. Dementia ranks as the seventh leading cause of death among diseases worldwide [1], and it can cause disability and dependence among older adults, which interferes with activities of daily living [2].

Early identification of dementia is crucial for effective treatment and timely intervention. Detection of the disease in its early stages can slow the progression and improve the quality of life for those affected. Moreover, it can help prevent the disease from developing into severe conditions. [3] MCI (Mild cognitive impairment) is considered a predecessor to dementia but does not significantly disrupt daily functioning [4]. People with MCI are at risk of progression to dementia [5]. Therefore, early detection of MCI offers an opportunity for monitoring, management, and intervention, which could help delay or prevent further cognitive decline [6].

Gait abnormalities can be early indicators of cognitive decline and a potential predictor of future dementia onset. Changes in walking patterns, such as slower speed, reduced stride length, or increased variability, have been linked to early signs of dementia [7]. Research showed that individuals with impaired gait are at a higher risk of developing cognitive impairment or progressing from MCI to other forms of dementia [8]. Moreover, dual-task gait assessments, which involve walking while simultaneously

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performing a cognitive task, challenge the brain to manage motor and cognitive assignments at the same time, offering deeper insight into cognitive function [9].

The Timed Up and Go (TUG) test is commonly used in clinical settings to assess a person's mobility, balance, and functional movement [10]. In this test, the individual is asked to rise from a chair, walk a short distance (usually around three meters), turn around, return to the chair, and sit down. A variation of this, known as the TUG dual-task (TUGdt) test, adds a simultaneous cognitive or motor task during walking. Examples of the TUGdt include counting backward, naming animals, or reciting the months of the year in reverse order.

This study aims to develop a non-invasive, video-based approach to predict the progression from MCI to dementia (2-year follow-up) using gait features extracted through pose estimation. Participants with MCI performed the TUG test under both single-task and two separate dual-task (TUGdt) conditions (1. naming animals, 2. reciting months in reverse order). Key mobility features such as joint angles, stride length, and walking speed were extracted and used to train machine learning models to distinguish between individuals who converted to dementia and those who didn't. This approach offers a cost-effective and simple method for early risk prediction, potentially aiding in timely intervention and monitoring of cognitive decline. To the best of the authors knowledge, this is the first study that examines early detection of dementia through pose estimation and machine learning [11,12,13].

2. Method

This section describes the methodology used for video recording, pose estimation, feature extraction, and prediction. The method involves of cleaning the recorded videos to isolate only the single-task and dual-task TUG segments, while cutting out any portions where participants were receiving instructions before the tests started. Pose estimation (using YOLOV8 with 17 keypoints extracted) is then performed on the curated clips, and the resulting keypoints (seen in the portrayal in Figure 1) are used to calculate features for the prediction model. These features are used to train models to predict individuals converted to dementia from MCI.

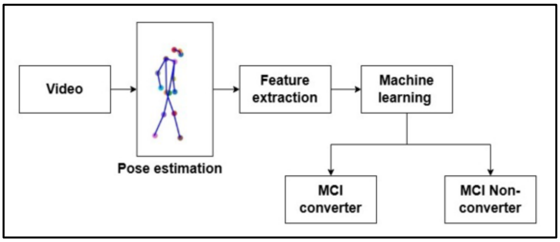

Figure1. Methodology workflow

2.1 Dataset

The data invoked in this research are extracted from the UDDGait™ project (UDDGait™: Uppsala-Dalarna Dementia and Gait Project - Dalarna University), which is a longitudinal study carried out in Sweden. The data were gathered at two clinics: Uppsala University Hospital (April 2015–February 2017) and Falu Hospital (June 2015–June 2016). A licensed physiotherapist conducted data collection [14]. The study was ethically approved by both the Regional Ethical Review Board in Uppsala and the

Swedish Ethical Review Authority (approval number: 2023-01670-01). All participants provided informed consent before contributing to the project.

The TUG tests were captured using two tripod-mounted video cameras. One camera was set up 2 meters in front of the turning point to record a frontal view, while the other was positioned 4 meters along the walking path to capture a side view. For this study, only the side-view was used.

The dataset used in this study comprises video recordings from 62 individuals diagnosed with MCI: 31 who later converted to dementia, and 31 were MCI at baseline. The 31 patients are the full population of the UDDGait™ project with conversion and the 31 that did not convert were randomly chosen from the pool of baseline MCI patients. Each participant completed one standard TUG test and two dual-task (TUGdt). In the first TUGdt, participants recited the months in reverse order while walking, and in the second, they named as many animals as possible during the walk. Table 1 summarizes the demographic characteristics of the two groups included in the analysis.

Table 1. Demographics of the dataset

Variable	Converter (31)	Non-converter (31)
Age, mean ±sd(cm)	74.45 ± 5.67	73.03 ± 9.08
Gender (M: F)	17:14	19:12
Height, mean ± sd(cm)	169.55 ± 8.77	169.29 ± 9.37
MMSE, mean ± sd	24.87 ± 2.80	25.71 ± 2.58

Sd: Standard deviation; HC: healthy controls; M: Male; F: Female; MMSE: Mini-mental state examination

2.2 *Feature extraction*

The gait features analyzed included velocity, acceleration, step count, cadence, stride length, total duration of the test, as well as knee and hip joint angles (eight features).

Velocity refers to how the body's center of gravity (COG) changes over time, measured by tracking its displacement across video frames within a specific time interval. Acceleration represents the change in velocity over time.

Step count during the TUG test was estimated by detecting peaks in the vertical (y-axis) movement of the ankle keypoints. Cadence was then calculated as the number of steps taken per minute.

Stride length, defined as the distance between two successive steps of the same foot, was determined by identifying the peak vertical positions of the left and right ankles; these peaks correspond to the highest point of each step. The horizontal gap between these peaks was measured and scaled into meters using a conversion factor.

Joint angles for the knee and hip were computed using a vector-based method. For the knee, this involved creating vectors from the hip to the knee and from the knee to the ankle, then applying the dot product to determine the angle between them. To account for individual variation in body size, all movement parameters were normalized relative to the participant's height.

2.3 Data Mining Method

This study employed three machine learning algorithms: support vector machines (SVM), logistic regression (LR), and extreme gradient boosting (XGBoost). Hyperparameters tuning was performed through GridSearch for all models. For this SVM setup, the optimal hyperparameters were RBF kernel, C = 10, and gamma = "scale. For logistic regression, maximum iterations are set to 1000 to ensure stable convergence. For XGBoost, the best configuration was n_estimators = 200, max_depth = 3, learning_rate = 0.2, subsample = 0.8, and colsample_bytree = 0.8. The models were trained and tested using 5-fold cross-validation for generalizability.

3. Results and Discussion

This study evaluated the potential of a video-based gait analysis method for predicting conversion from MCI to dementia. Three models were selected to cover linear and non-linear learning, while deep learning was excluded due to the limited sample size. XGBoost was selected due to its strong gradient boosting framework, ensemble-based approach, strong ability to model non-linear relationships, and built-in regularization that helps overcome overfitting. As a tree-based method, it was chosen over decision trees and random forest models. SVM was chosen for its capability to manage high-dimensional gait feature spaces and its ability to identify optimal decision boundaries between classes. Logistic regression was included as it is a linear model that works well in binary classification problems. The models were assessed using accuracy, precision, recall, and F1-score, ensuring a comprehensive evaluation of the predictive power.

Among the three models evaluated for predicting conversion from MCI to dementia, the SVM achieved the highest overall performance, with an accuracy of 70%, a recall of 68% (see Table 2). These results suggest that SVM was the most effective at identifying individuals likely to convert to dementia. XGBoost showed a comparable recall of 68% but slightly lower overall performance, with an accuracy of 65%. One possible reason for its underperformance compared to SVM is the limited sample size, which may have hindered XGBoost's capacity to generalize effectively. LR demonstrated the lowest performance across all metrics, with 63% accuracy and a recall of 62%. As a linear model, LR may lack the flexibility needed to capture the complex and non-linear relationships.

Table 2. Performance metrics of the models

Model	Accuracy	Recall	Precision	F1-score
SVM	70%	68%	71%	69%
XGboost	65%	68%	64%	66%
LR	63%	62%	64%	63%

In comparison to prior studies, this study focuses on the prediction of conversion from MCI to dementia using gait features, which is underexplored in earlier research. For instance, Tuena et al. [15] used gait profile and neuropsychological data (MMSE, DSST, TMT-B) with machine learning and similarly found SVM to yield strong results, aligning with our findings, but did not performed detailed gait feature extraction. Åberg et al. [11] found TUGdt (with video-derived step measures) to predict dementia conversion, but used Cox regression models rather than machine learning. These studies provide reference points against neuropsychological and traditional statistical predictors. Moreover, most existing gait studies, as highlighted in the systematic review by Al-Hammadi et al. [12], focus on classification tasks rather than prediction. Another systematic review by Javeed et al. [13] examined various machine learning approaches for dementia prediction across data types (images, clinical variables, voice), with limited exploration of gait-based prediction. This underscores the novelty and relevance of the approach in this study. To our knowledge, this is among the first studies to apply machine learning to video-derived gait features for dementia prediction. This study can serve as a complementary screening tool alongside existing clinical assessments.

4. Conclusion

This study evaluated the feasibility of using video-derived gait features for predicting conversion of MCI to dementia. Among the models evaluated, SVM demonstrated the highest predictive performance, achieving 70% accuracy. This study offers a simple, low-cost, and non-invasive approach for dementia onset prediction. The limitations include the small sample size and the dependence on the accuracy of the pose estimation model, which may affect feature precision. Additionally, deep learning approaches were not used due to the small dataset constraints. Future work should explore multimodal approaches, such as integrating features from speech and gait to improve the accuracy.

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