Early Detection of Fall Risks For Enhanced Elderly Care

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**Abstract.** Falls among older adults are one of the most important social health issues, with most occurrences leading to fracture, traumatic brain injury and long-term disability signiﬁcantly reducing quality of life, independence and future health care usage. Although it is useful to measure falls, the standard clinical assessment methods fail to identify the changes in movement patterns that major in falls and are urgently needed. An innovative method for prediction of fall risk is provided in this study through comprehensive analysis of six gait kinematic parameters (velocity, acceleration, GSI, cadence, step length and stride length) when performing the standardized Timed Up and Go (TUG) test. The methodology in the end makes use of state-of-the-art motion capture techniques and machine learning algorithms to take a unique approach to fall risk assessment. By human pose estimation, we can make precise tracking of 33 anatomical landmarks and get detailed quantitative data on motion dynamics, which are invisible to the naked eye. Once these kinematic measurements are collected, these are fed through very sophisticated classification algorithms that can detect patterns that are characteristic of differing degrees of fall risk. The addition of gait cycle detection improves assessment accuracy even more, as movements between the stance and swing phases are more critical to achieve balance and important for assessment purposes. Strong correlation with the widely used Fall Risk Assessment Tool confirms the reliability and clinical applicability of the method. Its advantages will be of earlier detection of the emerging mobility issues, a continuous monitoring capability and a quantitative monitoring of efficacy of intervention.

# **INTRODUCTION**

Falls are a major risk to older adults and have the potential to harm very severely and result in major loss of function and quality of life even with apparently minor injuries. To overcome this limitation, our work introduces a data driven approach based on a modified (extended) Timed Up and Go (TUG) test using motion analysis aided by AI. Using this validated clinical tool, the amount of time it takes for an individual to stand, walk, turn and sit is measured, serving as a basis to further analyze [1].

The method makes use of MediaPipe Pose to track body key points which generate movement-related data. The AI algorithms which operate from Random Forest models analyse the key points to calculate gait parameters that include walking speed together with stride variability and turning dynamics and postural stability metrics. The evaluation strategy analyses specific metrics to detect movement patterns that signal possible fall risks for older adults. provide better quantitative assessment of gait and balance based on posture estimation for data driven insights to make personal interventions [2].

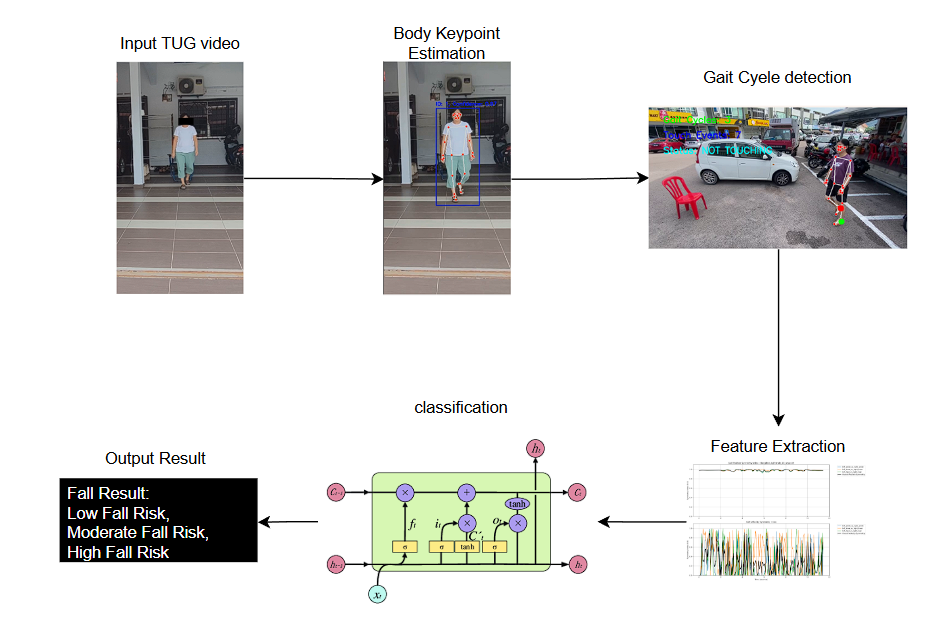
In 2019, Yang et al. [1 – 7] proposed a vision-based fall detection system in which convolutional neural networks (CNNs). Main dataset was the UP-Fall Detection dataset from 17 healthy subjects undertaking varied activities and falls, measured with multiple cameras. The CNN model was to identify and analyze images in fixed time window and extract features that use the optical flow technique: the motion differential between two successive images. This ended with the last outcome that the presented multi vision-based method was accurate to the 95.64% detection of human falls to prove the efficiency of the approach.

Kim et al. [4], developed a fall risk assessment system by using multiple ML including (Decision Tree, AdaBoost, et cetera) models on depth images from 30 elderly patients, recorded with Kinect sensor. By tracking daily activities, the parameters of steps taken, and standing time were collected to classify patients as high or low risk. They achieved perfect accuracy with all the best models suggesting that potential of home monitoring for fall prevention.

In 2022, Eichler et al. [3] developed an automated fall risk assessment system based on Random Forest and SVM classifiers by loading dataset of 130 participants. Skeletal sequences were captured by a multi-camera setup performing BBS tasks and spatiotemporal features were extracted in this system. Their Efficient-BBS (E-BBS) system achieved 97% accuracy while reducing required tasks from 14 to 4–6 (prevention) or 6–14 (assessment), still 97%, saving time and resources through splitting of BBS tasks into separate Random Forestï¿½ models and use of SVM for final prediction.

# **PROPOSED SOLUTION**

The proposed fall risks detection approach involves several key steps: data collection, body key point estimation, data preprocessing, Random Forest model training, and result classification. Data collection is performed through the Timed Up and Go (TUG) test that determines the fall risk and mobility by measuring the time it takes for a person to get up from a chair, walk for three meters and turn around, walk for three meters, and sit down. Using MediaPipe Pose Landmarker, the study detects and tracks human motion in recorded videos, saving the estimated body key points into JSON files. These processed data are then used to train a Random Forest model, which classifies the degree of fall risk. An overall workflow of this pre-categorization is illustrated in Figure 1. Considering that, Random Forest is preferred as it is robust to complex dataset and gives interpretable risk classifications.



**Figure 1.**Block diagram of the proposed method

## **DATASET**

When collecting videos, we will give priority to demonstrating the full TUG. After the test process ensures that they have understood the whole process, we will start filming. Sit on the chair before we start. When we say "Start", stand up and walk 3 meters forward, then turn around and walk back to the chair and sit down. During the shoot we will use two mobile phones and tripods. One is to shoot the front of the volunteer in Figure 2 and the other is to shoot the side of the phone Figure 3. We make sure they are ready before we start and give them signal values until they have gone through the whole test and then we stop the video.

Each participant is required to fill a survey form prior to data collection. The survey form is divided into three parts. The first part is the Consent Form, the second part is the Respondent's Consent, and the third part is the Fall Risk Assessment Tool Score. The main purpose of the consent form is to make sure that the volunteer understands what we are going to do. The test is about gait or walking and understanding what the main content of this test is to let them understand how the whole process works. The Respondent's Consent mainly collects personal information. The Fall Risk Assessment Tool Score is to ask the volunteer to answer questions about the TUG to calculate the volunteer's risk index.

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| **Figure 2.** Sample of subject acquired from front angle | **Figure 3.** Sample of subject acquired from side angle |

## **HUMAN POSE ESTIMATION**

In this study, MediaPipe Pose Landmarker is used for human pose estimation in TUG test videos. This ML-based solution detects 33 body landmarks from 2D/3D video inputs, enabling accurate motion analysis and action classification. Key point estimation processes 2D/3D visual data to predict spatial coordinates (x,y,z) of structural features. In human pose estimation, it detects anatomical landmarks like joints (shoulders, elbows, knees) and connects them to create a skeletal representation. This skeleton model enables movement analysis, posture assessment, and action recognition. The technique is fundamental for applications requiring motion tracking or biomechanical evaluation [4].

The midpoint is calculated as in Equation (1).

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The weighted average estimation is computed as in Equation (2).

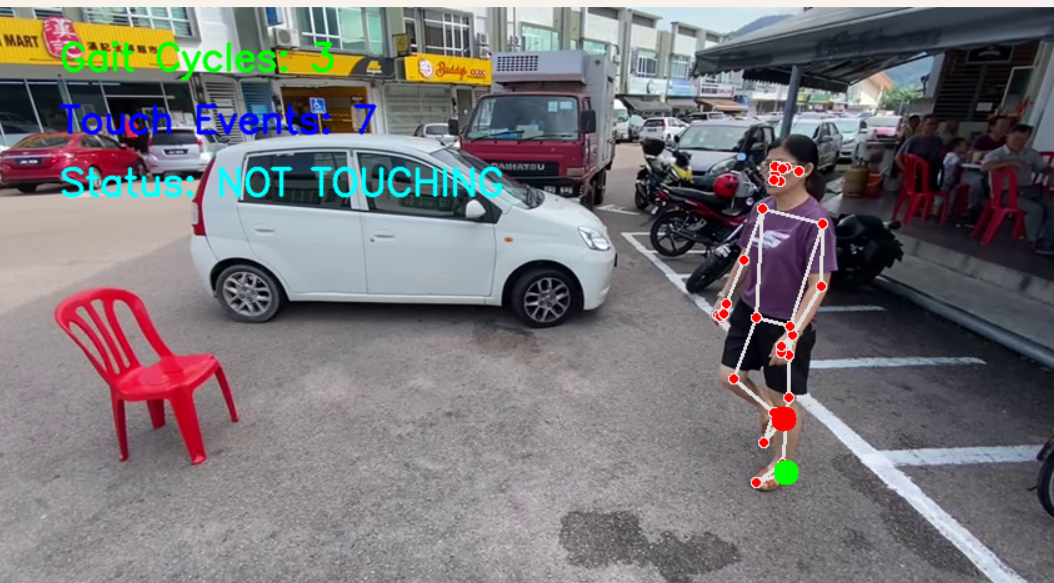
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Figure 4 illustrates the gait cycle detection process during video-based body motion analysis. Contact points are monitored between left and right heels, a cycle detection is triggered when one of the heels makes ground contact. During these detected gait cycles, the system captures and records all relevant body key point data (joint positions, angles, etc.) into a structured JSON file. The spatial and temporal movement patterns for each complete stride of each subject are output to this JSON object for further analysis of gait parameters such as step length, cadence, symmetry, and so on.

## **FEATURE EXTRACTION AND CLASSIFICATION (RANDOM FOREST)**

The extraction phase plays a critical role in transforming raw motion data into meaningful gait parameters that can be used for fall risk classification. The features extracted include Acceleration, Velocity, Gait Symmetry Index, Candence, Step Length and Stride Length. The combine acceleration computes the first derivative (velocity) and second derivative (acceleration) from the smoothed coordinates. The combined acceleration is obtained by averaging the magnitudes of all tracked key points, shown in Equation (3).

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**Figure 4.**Gait cycle detection

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**Figure 5.**Acceleration

Velocity is derived by applying a gradient function to the smoothed *X* and *Y* positions of the key points, then computing the magnitude (see Equation (4)). The combined velocity is the average of all tracked points (e.g., ankles, hips) shown in Figure 5.

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**Figure 6.** Velocity

The Gait Symmetry Index (GSI) is calculated by comparing the vertical positions and velocities of corresponding left and right lower-body key points as shown in Figure 6 (ankles, knees, heels) using the Equations (5) and (6).

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| --- | --- |
| Position Symmetry Index: |  |

|  |  |
| --- | --- |
| Velocity Symmetry Index: |  |

The cadence is calculated by walking (steps per minute) by analysing vertical ankle movements from motion capture data, first smoothing the positional data using a Savitzky-Golay filter to reduce noise, then detecting steps as local minima in the ankle trajectories (when feet are at their lowest point during mid-swing) as displayed in Figure 7. For each detected step, it calculates the time intervals between consecutive steps and derives both instantaneous cadence (60/interval) and average cadence across all steps.

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AI-generated content may be incorrect.

**Figure 7.**Gait symmetry index

The code calculates step length as the horizontal distance between opposite feet during consecutive strikes (left-right or right-left transitions). It uses smooth ankle positions and detects foot strikes calculated in Figure 8 (local minima in vertical motion) and is calculated as in Equation (7).

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**Figure 8.**Candence over time

The stride length represents the horizontal distance covered between two consecutive ground contacts of the same foot during walking as shown in Figure 9. The code calculates this by first detecting foot strikes (local minima in vertical ankle motion) and then measuring the absolute horizontal distance between positions of the same foot (left or right) at consecutive strike points using the Equation (8),

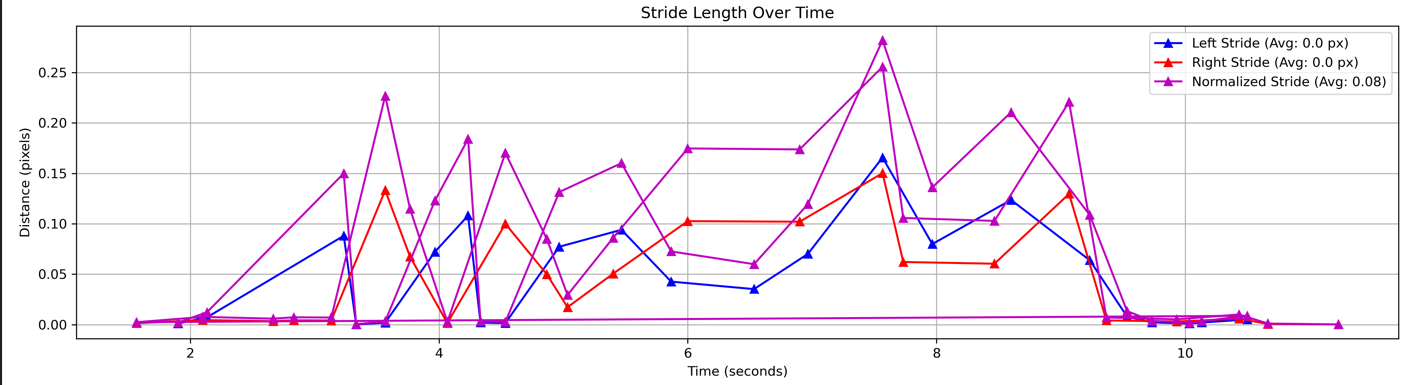
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**Figure 9.**Step length over time

Random Forest is an ensemble learning method that uses bagging to combine multiple decision trees. It outputs either the most frequent class (classification) or average prediction (regression) across all trees as displayed in Figure 10. Unlike sequential models, it handles both numerical and categorical data effectively. The algorithm is robust against overfitting while maintaining high accuracy. Applications span medical diagnosis, financial analysis, and industrial systems. Advantages include handling high-dimensional data and providing interpretable results. The method remains popular for its reliability with diverse real-world datasets [5].



**Figure 10.**Stride length over time

# **EXPERIMENT RESULTS**

Table 1 shows a classification report for a fall risk prediction Random Forest model, where Class 0 (Low Fall Risk) and Class 1 (Moderate Fall Risk) are evaluated. The model achieves an overall accuracy of 77%, with precision (correct predictions) at 78% for Class 0 and 78% for Class 1, and recall (actual cases identified) at 68% for Class 0 and 83% for Class 1, indicating better performance in detecting high-risk patients. The F1-scores (0.71 for Class 0, 0.81 for Class 1) and balanced accuracy (75.8%) suggest the model is moderately effective but could improve in reducing false negatives for low-risk cases while maintaining its strength in identifying Moderated-risk individuals.

**TABLE 1.** Performance of the proposed fall risk prediction method

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| **Classifier** | **Precision** | **Recall** | **F1-Score** |
| 0 (Low Fall Risk) | 0.78 | 0.68 | 0.71 |
| 1 (Moderate Fall Risk) | 0.78 | 0.83 | 0.81 |

# **CONCLUSION**

This study successfully developed a technology-enhanced fall risk assessment method centered around the Timed Up and Go (TUG) test, leveraging advanced motion analysis and artificial intelligence to improve the accuracy and predictive capability of fall risk detection in the elderly population. By integrating MediaPipe Pose Landmarker for body key point estimation and employing a Random Forest classifier for gait feature analysis, the system achieved an overall accuracy of 77%, with strong performance in identifying moderate fall risk cases (precision: 78%, recall: 83%, F1-score: 0.81).

The results demonstrate the potential of combining video-based motion tracking with machine learning to overcome the limitations of traditional fall risk assessments, such as subjectivity and infrequent testing. The system’s ability to extract and analyses gait parameters—such as stride length, cadence, and velocity symmetry—provides a more objective and dynamic evaluation of fall risk, enabling earlier intervention.

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