Automated Frailty Detection in Geriatric Health

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**Abstract.** One of the most prevalent geriatric syndromes among elderly people exists as frailty which leads to negative outcomes including hospitalization and cognitive decline and falls among others. Regular methods used for evaluation require too much time and produce results that cannot scale up effectively. This research seeks to determine whether artificial intelligence (AI) combined with video-based gait analysis methodology could serve as an appropriate tool for frailty assessment among elderly people. The participants completed the standard Timed Up and Go test and received their frailty ratings through using the JFRET (Japanese Frailty Evaluation Tool). Human pose estimation methods helped extract anatomical points from the body which enabled computerized calculations of critical gait measurements consisting of stride length together with speed and balance motion control. The 1D Convolutional Neural Network (CNN) model executed frailty classification operations. This investigation delves into extensive correlation assessment of gait features with frailty scores which enables better understanding between frailty severity and movement characteristics. The model's performance along with its generalizability will improve when future work expands the dataset. Research goals target both the best frailty classification algorithm development and the establishment of AI-based gait technologies to detect frailty in an early manner together with reproducible efficiency. The approach shows practical potential as a method to enhance senior healthcare results in medical practice.

# INTRODUCTION

Frailty functions as a common geriatric syndrome that makes elderly people unable to perform everyday activities which elevates their risk of negative health events including hospitalizations and cognitive decline and falls [1 - 4]. The assessment of frailty at an early stage enables healthcare professionals to implement necessary interventions that minimize health hazards and boost patient life quality and lighten the healthcare load. The assessment tools for frailty currently in use require substantial resources and consume major time while offering limited potential for broad implementation.

This study combines video-based gait analysis with artificial intelligence for developing innovative automated frailty detection. The model analyzes essential gait parameters that include stride length and walking speed and balance data gathered during the well-known Timed Up and Go (TUG) test [5] which serves as a main clinical assessment for mobility and frailty. Human pose estimation techniques is used to obtain anatomical key points that come from participant video recordings of their TUG test execution. The CNN model performs frailty classification on calculated critical gait metrics derived from extracted key points. The study examines gait characteristics to create an accurate detection tool that separates participants into three frailty groups including non-frail, pre-frail and frail individuals. The model provides accessibility by removing mandatory specialized wearable sensors and complex setup demands due to its utilization of video data.

Abbas and Le Bouquin Jeannès [6] employed handcrafted gait features and various machine learning classifiers for acceleration-based gait analysis to assess frailty. Their study utilized the GAnFA1 dataset (ActFreeLi and WWBS Metrics) and achieved an accuracy of 88.5%. This method improves the efficiency of assessment and reduces the consumption of resources, but the availability and functionality of wearable sensors might be a problem for some elderly people. Prior research on gait analysis has focused mainly on the temporospatial characteristics of gait including speed, stride length and frequency in a more supervised fashion in order to assess frailty in a population of older adults. New-generation wearable sensors can gather acceleration data in real-life contexts to assess gait variability and other indices of frailty. From the obtained gait parameters, machine learning models have been trained to estimate the frailty level, and the corresponding patterns have been established. However, one shortcoming in existing gait literature is that comprehensive gait parameters evaluation in unsupervised context and frailty has not been discussed in detail, it is recommended that further research employs a range of features to improve the accuracy of frailty prediction models.

In 2023, Senigagliesi et al. [7] used deep learning for telemonitoring of frailty using cross-validation and confusion matrices for assessment. They employed the MediaPipe Holistic dataset and got a high accuracy of 92.8%. They adopted this approach where activity recognition is conducted using LSTM networks and the method is accurate. However, supervising videos about it at different time intervals could potentially breach the privacy. Prior studies in HAR have demonstrated the use of machine learning for health status analysis, Human gait and Gesture recognition. New studies have established the applicability of sensors and machine learning to the evaluation of Alzheimer’s patients’ mental status and the management of their activities. It is argued that machine learning systems for health monitoring have been proven useful especially for detection of daily experiences and mental health monitoring and also practice the use of sensors to capture data for analysis. Besides, investigation has been done on other environmental and localized sensors to observe personal hygiene activities that are imperative in frailty assessment. These sensors enable a timely detection of these problems and the appropriate measures to be taken. LSTM networks have been successfully used for the predicting the daily activities and dependencies between time-series data, which makes LSTM useful for monitoring actions like washing face, brushing teeth, and combing hair. This brief literature review outlines areas of related work that are relevant to the current study and inform its application of LSTM networks and camera sensors for identifying frailer individuals through hygiene activities.

# PROPOSED SOLUTION

## Data Collection

Participants of over age 60 are invited performed the TUG test while being filmed from two angles. A survey assessed exhaustion criteria to categorize participants into frail, pre-frail, and non-frail groups. Figure 1 depicts some sample videos containing frail, pre-frail and non-frail individuals.

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| --- | --- | --- | --- |
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|  |  |  |  |
|  |  |  |  |

**FIGURE 1.** Sample videos of frail (first row), pre-frail (second row) and non-frail (third row) individuals

## Gait Cycle Detection

Two gait cycles are selected from every participant to form a proper statistical gait representation. This results in a total of 104 samples, derived from 52 participants with two cycles each. Gait cycles were detected by tracking the movement of foot landmarks (left and right feet) from video recordings. Gait cycles start at the moment a foot begins its movement through a motion such as heel strike until that same foot reaches the finish point of its stride. The duration of a gait cycle was calculated as the difference between the end frame and start frame. The study rejected cycles whose duration exceeded more than 0.5 seconds to 3 seconds because these ranged outside physiological limits.

The duration of a gait cycle is calculated by measuring the time between the start and end of the cycle, shown in Equation (1). If the cycle is eliminated from additional processing when its duration calculation results in values outside this predefined range:

|  |  |
| --- | --- |
|  | (1) |

Essential features are extracted from the gait cycle and used as inputs for the 1D CNN model to classify frailty levels.

## Feature Extraction and Classification

In this study, MediaPipe Pose is used to extract 33 key landmarks from the acquired videos. Distances between joints, velocities, and accelerations were computed from these body key points to derive the corresponding gait parameters. To analyze the relative movement of the body, distances between specific body joints are calculated. The distance between the left shoulder and the right shoulder is computed as in Equation (2).

|  |  |
| --- | --- |
|  | (2) |

Stride length is computed as the maximum distance between the left and right foot, shown in Equation (3).

|  |  |
| --- | --- |
|  | (3) |

Symmetry, which quantifies the balance of movement between corresponding body parts, is calculated by measuring the difference between the left and right feet (or any other relevant joint pairs, such as hips). One way to calculate foot symmetry is shown in Equation (4).

|  |  |
| --- | --- |
|  | (4) |

where *N* represents the number of frames taken during the gait cycle. The symmetry calculation can also be applied to other joint pairs to capture different aspects of symmetry. The extracted features (e.g., stride length, symmetry) were input into a 1D CNN model for frailty classification (refer Equation (5)),

|  |  |
| --- | --- |
|  | (5) |

where .

The gait features support effective frailty status classification through convolutional layers which use different filters together with kernel sizes of 5 and 3 in their series. The input data receives hierarchical feature extraction from different filters (64, 128, and 256) one layer uses each number of filters for analysis. Non-linear extraction in data occurs through the use of Rectified Linear Unit (ReLU) activation functions during the hidden layer process. In the final layer, softmax activation is used to generate probability distributions for the three frailty categories (non-frail, pre-frail, and frail).

Multiple sequential convolutional layers with varying receptive fields enable the network to obtain different abstract levels from the input gait features. These layers are followed by max-pooling operations, which reduce the dimensionality of the feature maps while retaining the most important information, thus improving the computational efficiency of the model. The network learns accurate predictions for frailty status through graded activation processing together with max-pooling and dropout operations even when operating with restricted labeled data. Through this combination of convolution, activation, max-pooling, and dropout operations, the network learns to make accurate frailty status predictions from gait movement patterns, even in the case of limited labeled data.

# EXPERIMENTAL RESULTS

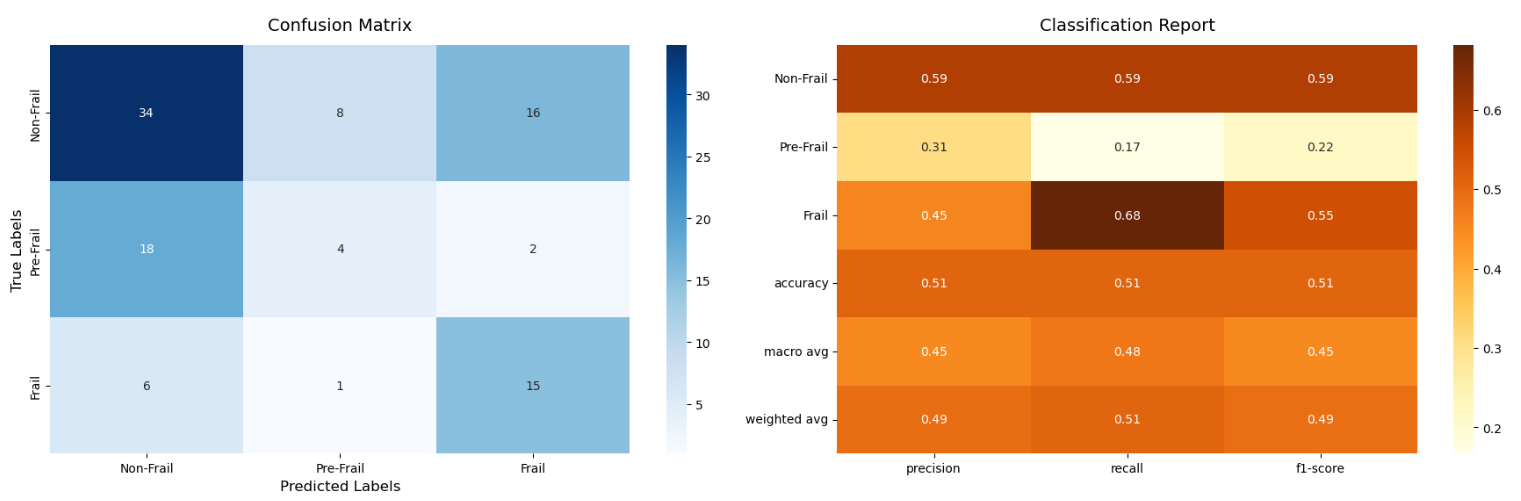
## ****Classification Accuracy****

The model processed 104 samples from 52 participants. The classification accuracy is presented in Table 1. The model showed moderate success and has difficulty distinguishing between frail and non-frail individuals. The confusion matrix is depicted in Figure 2. It highlights some misclassifications between the frail and non-frail groups, where frail individuals were predicted as non-frail or pre-frail. The classification report also provides a detailed breakdown of the model's performance for each frailty group. The model exhibits better success rates at identifying non-frail individuals than frail individuals based on its higher precision and recall metrics for that category. The model faced difficulties recognizing frail individuals because the precision and recall performance results were lower than those of other groups.

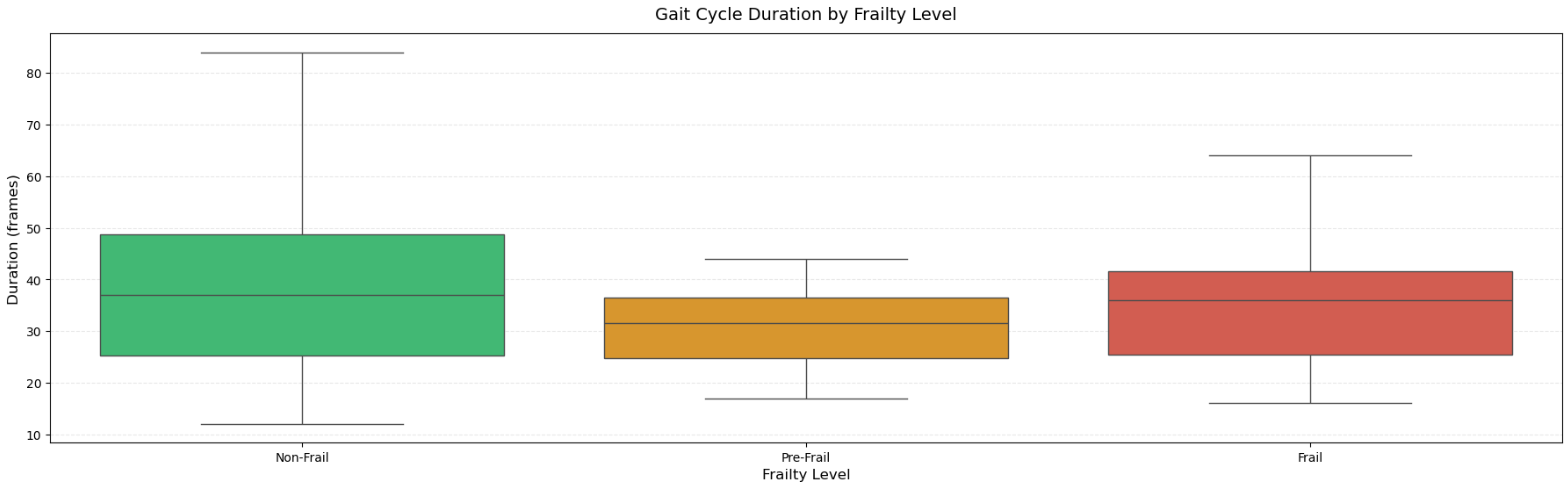
Visualization of the gait cycle duration for different frailty levels is provided Figure 3, with Frail participants having the longest duration. This supports the hypothesis that frailty is linked to slower, more variable gait. The histogram presented in Figure 4 shows the distribution of prediction accuracy of the participants. The majority of participants show lower prediction accuracy, with a few showing higher accuracy. The red line represents the mean accuracy of 0.51, indicating that the model's performance varies considerably across participants.

**TABLE 1.** Classification accuracy

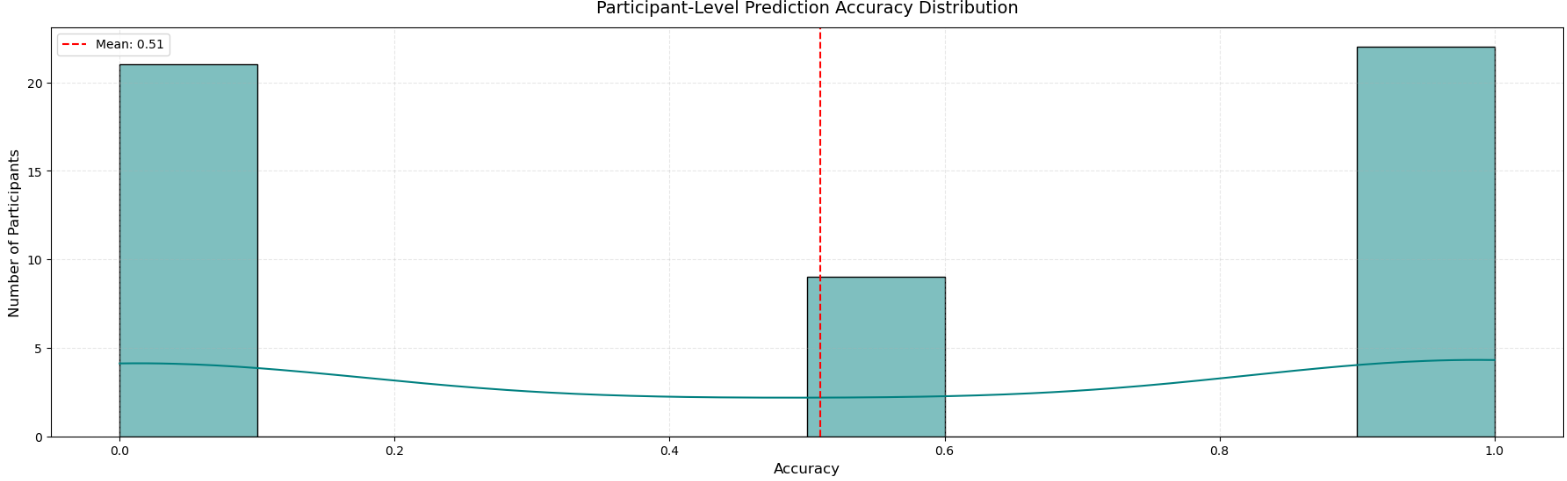
|  |  |
| --- | --- |
| **Metric** | **Value** |
| Accuracy | 51% |
| Precision | 45% |
| Recall | 48% |
| F1-Score | 45% |
| Pearson Correlation | 0.2422 |
| Pearson P-Value | 0.0133 |



**FIGURE 2**. **Confusion Matrix and Classification Report.**



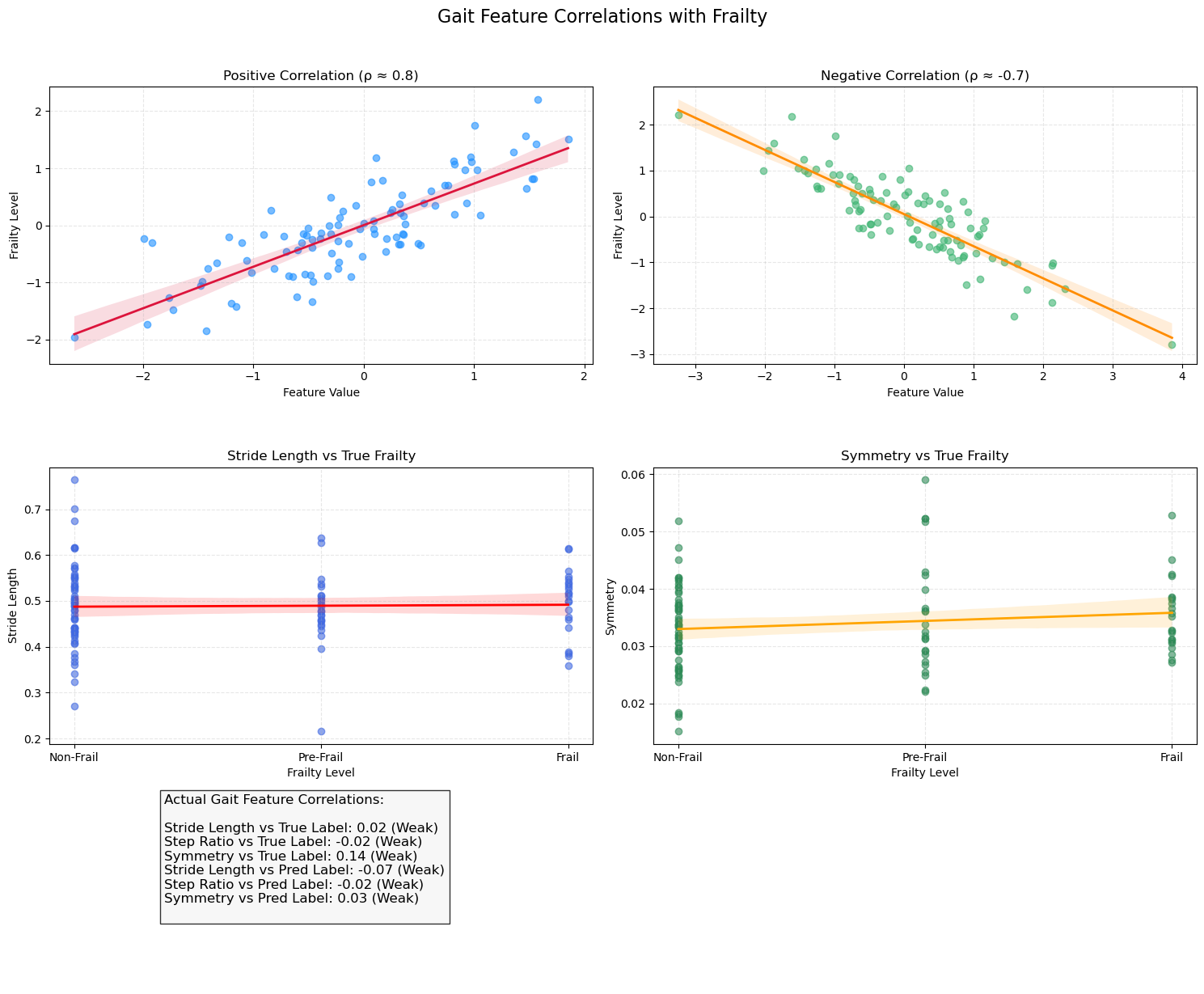
**FIGURE 3.** **Gait Cycle Duration by Frailty Level.**



**FIGURE 4. Participant-Level prediction accuracy distribution**

## ****Feature Correlations Analysis****

The correlations between gait features and frailty levels are analyzed and illustrated in Figure 5. The figure displays the correlation between various gait features and frailty levels. The positive correlation plot (p ≈ 0.8) indicates a strong relationship between a particular gait feature and frailty level, suggesting its potential as a predictor. The negative correlation plot (p ≈ -0.7) shows an inverse relationship, where an increase in the gait feature corresponds to a decrease in frailty.



**FIGURE 5.** **Gait feature correlations with frailty**

# CONCLUSION

Frailty negatively affects elderly people's capability to carry out daily tasks which raises their risk of health decline. The early identification of frailty enables preventive measures that protect hospital admissions and improve daily functioning of patients. Standard assessment procedures consume plenty of resources while requiring extended periods to complete. This research explores the automatic detection of frailty by employing AI-powered video-based gait analysis on stride length together with walking speed and balance measurements collected during the TUG test. Experimental results demonstrate its potential to be implemented in real-life applications. In the future, more samples of individuals with different frailty levels will be collected. Besides, more sophisticated algorithms will be explored to correlate the gait features with the frailty levels.

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