Wearable Technology & Mobile Perception for Monitoring Stability in IADLs in Older Adults with MCI

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Background

- Mild cognitive impairment (MCI) is a condition characterized by a decline in cognitive function greater than what would be expected for an individual's age and level of Education [1]
- MCI will increase the risk of falling: an odds ratio of 1.98 and a 95% confidence interval of 1.11-3.53 [2]
- Falls are a serious concern:
  - Lead to debilitating injuries: broken bones and head injuries [3]
  - Significant financial impact: average cost of $62K~$64K for a fall or fall with any injury [4]
- Current cognitive-motor dual-task tests is promising in predicting MCI and related falls but lacking real-world daily environment.[5]
- Deep learning (DL) methods have shown very promising result on the action recognition task. [6]
- Introducing DL methods into the previous doctor-led cognitive-motor dual-task test can greatly save doctors' energy and reduce clinical costs

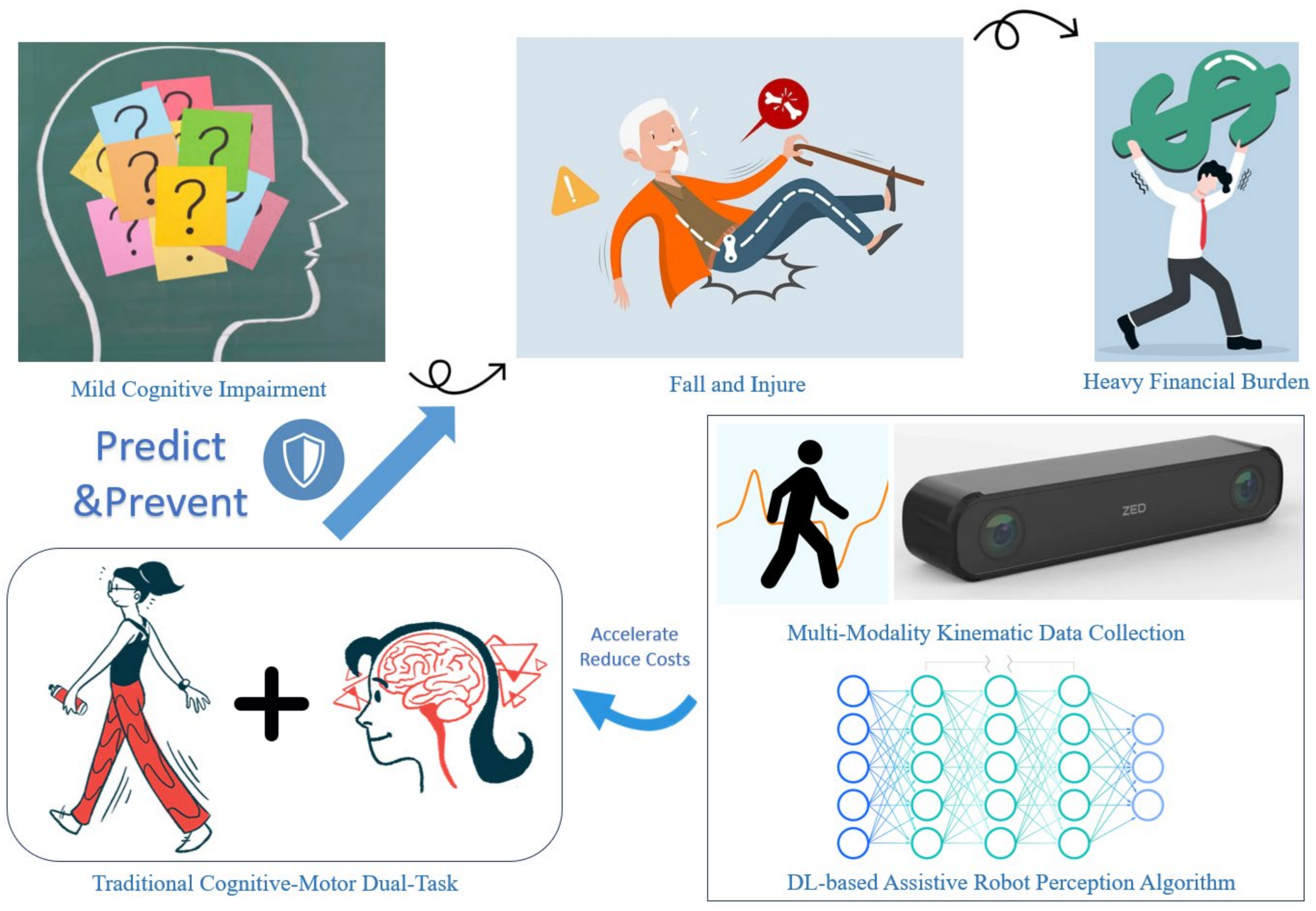

Fig. 1: Research Motivation.

Research Purpose

- Hypothesis: The kinematic and visual data collected by the inertial measurement unity (IMU) and depth camera when the subject perform real-world cognitive-motor dual-task contain enough information to do the further behavior analysis.
- Aim: Develop and train a DL framework in the real-world daily environment and propose feature extraction algorithms to automatically recognizing and determining differences in naturalistic movements for older cognitively healthy adults and those with MCI.
- Significance: By identifying differences, we may identify possibly interventions that ultimately reduce their risk of falls

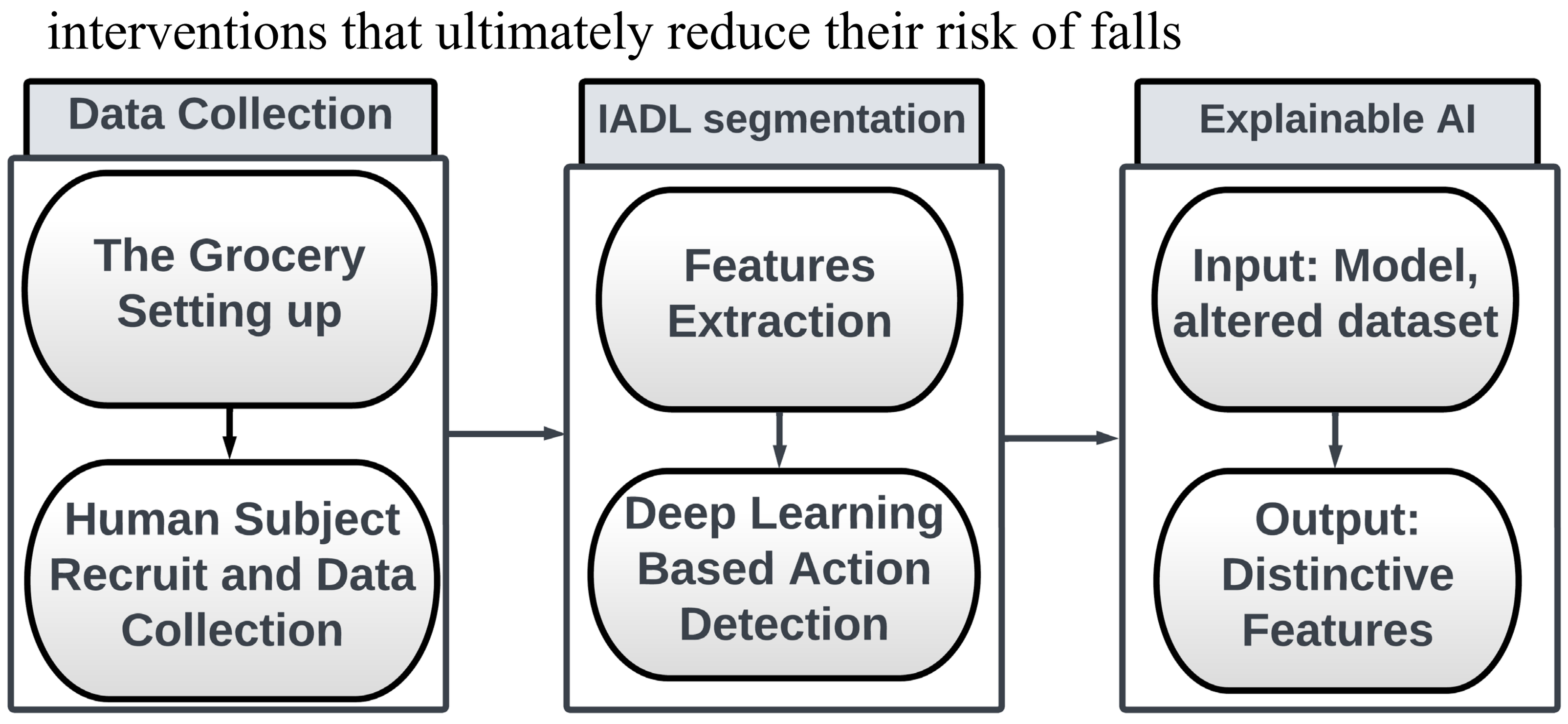

Fig. 2: The General Design for Our Research

Methods

❖Data collection

- A simulated grocery store was constructed in order to collect IADL kinematic data for the human subjects.
  - Grocery shopping requires both cognitive abilities and motor skills. It is a good real-world daily environment cognitive-motor dual-task tests.
- Description of the subjects
  - Number of subjects:
    - 20 MCI subjects
    - 20 cognitively normal subjects
  - Diversity: The subjects include African, Caucasian, Asian, etc.
  - Age distribution: The subjects' ages range from 55 to 80 years old.
- Data modalities:
  - Kinematic data:
    - 4 IMUs for each subject: Head, lumbar region, left and right foot.
    - Each IMU housing three sensors: accelerometers, gyroscopes, and magnetometers
  - Visual data:
    - One first-person point-of- view action camera
      - Anti-shake function
      - Mounted on the subject's chest to capture ground truth actions
    - Two third-person point-of-view depth cameras
      - Depth sensor to capture 3D information
      - The scope of them covers the entire self-built grocery store

❖Deep Learning IADL recognition Model

- Multimodal DL perception model:
  - Aim: Classify the instrumental activities of daily living (IADL)
- Video Data Processing for IADL Recognition
  - We will try both CNN and transformer-based architecture to find the best solution. The model's output will be a 1D feature vector
- IMU Data Processing for IADL Recognition
  - Signal denoise: Fourier transformation
  - We will employ either a CNN-based deep learning model [12] or a transformer-based deep learning model.
  - Output should be a feature matrix

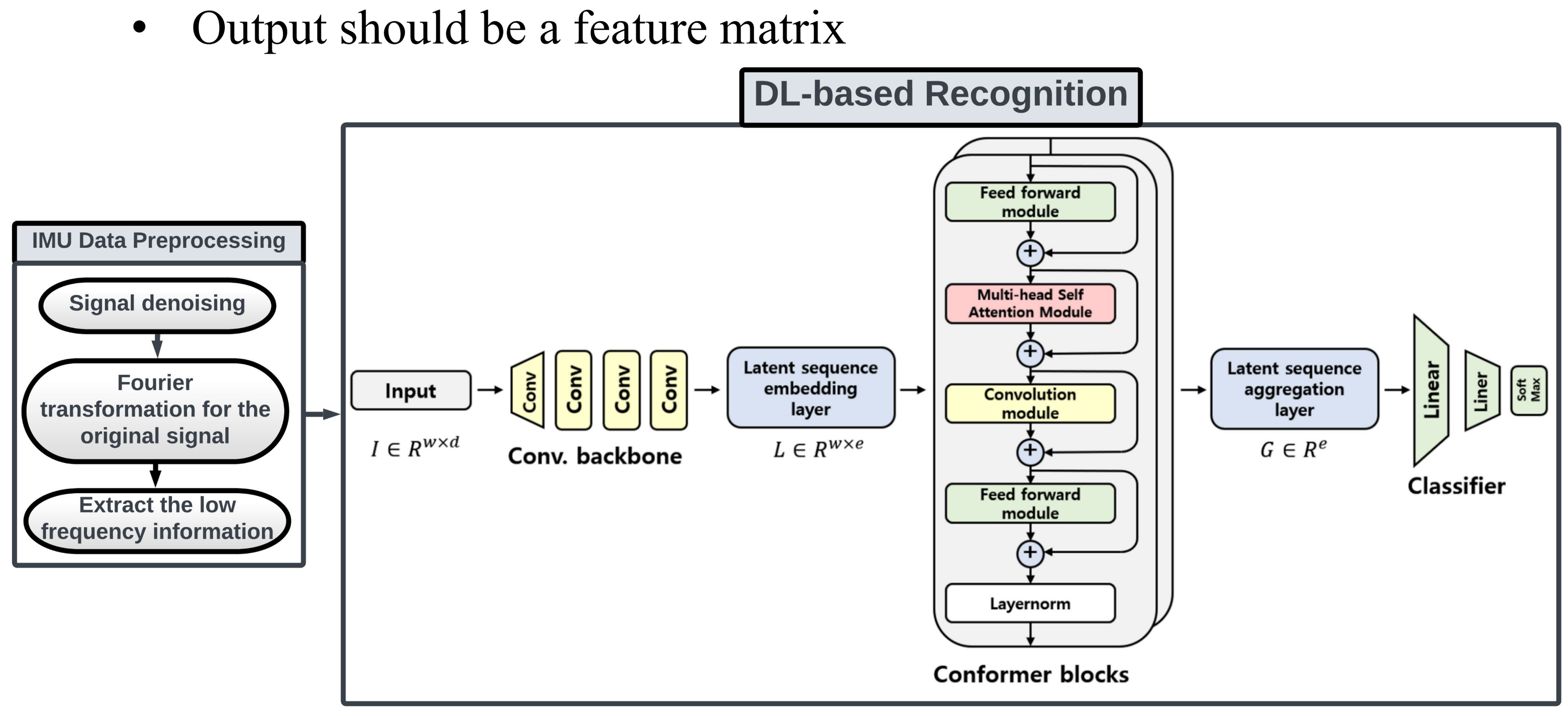

Fig. 3: IMU Data Processing for IADL Recognition.

- Feature Fusion and Multi-Modal Recognition
  - Matrix concatenation and fully connect neural network as baseline
  - Explore more advanced feature fusion techniques such as transformer

❖Explainable AI

- Extract features from the healthy and MCI subjects' movement
- Temporal and frequency domain features of gait and non-gait movements will be analyzed.

Initial Results

Fig. 4: Top left: First-person point-of-view camera view; Bottom left: third-person point-of-view camera view; Top right: Frequecy domain of the original IMU signal; Bottom left: skeleton movement tracking for the subject shopping..

References

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