EBP Phase 2

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I. **Introduction:** Maintaining safety for the growing number of older adults has been a challenge due to a shortage of residential care, and emerging health conditions. As the United States continuously faces a growing population of older adults, technology advancements are being studied to help monitor health status. With a shortage of caregivers, nurses face challenges in early identification and prevention of mobility changes within older adults. Traditional fall risk assessments have been used to help monitor fall, often relying on baseline information. However, they don't help get down to the root of potential health problems and are unable to gather real changes in mobility and gait in preceding falls. In addition, they often require direct clinician involvement. When faced with these challenges, an advancement in technology allows data to be collected from a machine approach to learn gait and mobility patterns. This approach involves using in-home sensors to collect raw data and deviations. This approach, known as the unsupervised anomaly detection, uses an autoencoder to flag deviations or "anomalies" in an individual's normal gait pattern. When using the unsupervised anomaly detection and machine learning, falls can be detected indirectly, while at home, through motion and gait changes. This detection system works alongside the electronic health record (EHR) to document real-world data to predict falls.

   a. Use of an anomaly detector

      1. Machine learning device (Artificial Intelligence) that monitors a person's "normal" data, such as gait. When data is off, it is flagged as an anomaly. This process helps predict future events from past data.

b. Collecting health status using innovations within technology.

1. Technology advancements allow for in home data collection using light sensors, infrared motion sensors, water sensors, smart carpets, wearable, and contact sensors.

II. **Purpose:** The purpose of this test is to determine if the use of machine learning methods can detect a fall up to 10 days before one happens by analyzing data in an at home setting, rather than utilizing direct clinician care.

III. **Method**: This research design used a pilot study in analyzing how artificial intelligence (machine learning) could detect anomalies in falls and use that data to predict future fall risk in older adults. Over 11 months, real-world in-home sensor data was analyzed in one older adult participant who lived independently. Data collected was sourced in two different measurements: unobtrusive in-home sensor data and the electronic health record (EHR). This pilot study's targeted outcome variable was based on the diagnosis of a fall, labeled as the initial encounter. The initial encounter is described as when a participant is actively seeing a provider for treatment following a fall. However, any previous history of halls or fall diagnosis are excluded due to having no representation of the current fall. After the initial encounter, the target outcome was extended to a 10-day window prior to the current fall to recognize and analyze the indicators of fall risk. Along with collected data from sensors and the EHR, the primary independent variables used were gait characteristics. The anomaly detection machine was set to train 60 days of the participants data to understand normal gait and fall behaviors and patterns. The remaining 255 days were used to observe fall risks, determine anomalies, and analyze fall risk indicators.

a. Pilot Feasibility Study

1. Pilot study is designed to collect real data in determining fall risk using anomaly detection.

b. Participant

1. One older adult who was aging in place.
2. Monitoring was continuous to collect and analyze one individual's pattern in gait.

c. Time Frame
    1. Data collected began January 22, 2020, and completed on December 1, 2020.
d. Use of real in-home data
    1. Data collected involved using real in-home information from sensor data, instead of using stimulated data.
    2. EHR documentation contributing health information.
        a. Medical history
        b. Diagnoses
        c. Medications
        d. Labs
        e. Clinical observations
        f. Height
        g. Weight
        h. Vital signs
        i. Diagnostics
        j. Confirmation in identifying fall events.
e. In-Home sensor data
    1. Hydraulic bed sensors
    2. Passive infrared motion sensors
    3. Depth cameras
f. Gait independent variables used
    1. Time spent in bed (seconds)
    2. Time restless in bed
    3. Pulse rate
    4. Respiration rate
    5. Walk speed

6. Height
7. Stride length
8. Stride time

IV. **Results**: In this study, accuracy is not the best elevation of the model due to the imbalance of falls in the dataset since predicating "no fall" most of the time can inflate accuracy. The F1 score, on the other hand, better showed the balance of precision and recall. When it is paired with the ROC-AUC score, the precision and accuracy scores show a good way in distinguishing true positive, false positive, and false negatives. The Bier score shows that the models' predications were well calibrated. Overall, showing that the anomaly predication model can improve identification of fall risk by the success within the 10-day period.

a. In figure one shows a line plot of the 59,505 individual readings of gait characteristics from February 2020-July 2022 that included height, walk speed, stride time, and stride length. During 2020, two fall events were recorded in October, and the model was trained using data from that year.

b. In figure two, by using the data collected in figure one, it records the anomaly scores, prediction, 10-day prior window, and actual fall diagnoses.

c. After being trained on 60 days of sensor data, the autoencoder model detected fall-related anomalies within the 10-day window with strong performance. The model achieved:

   i. Accuracy: 0.96
   ii. F1 Score: 0.78
   iii. ROC-AUC: 0.89
   iv. Brier Score: 0.04

Fall Safety of the Future!

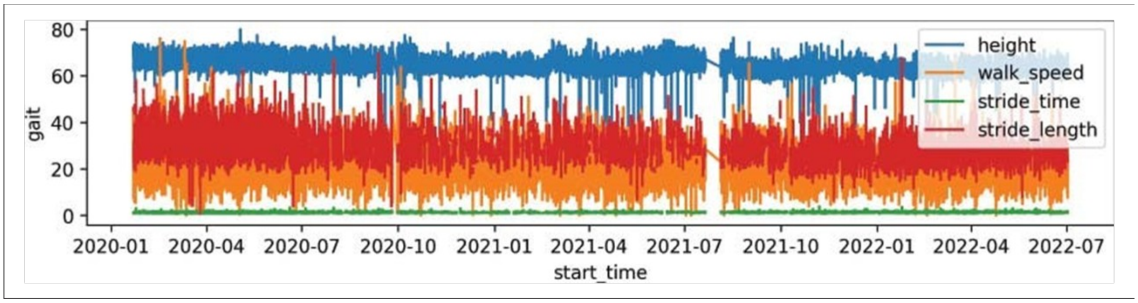

Figure 1: Time series line graph of gait sensor data.

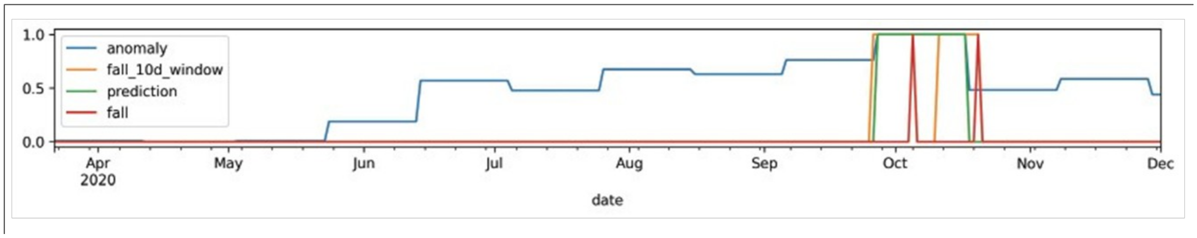

Figure 2: Visual output of anomaly detector results.

V. **Conclusion:** Core nursing priorities involve client safety, prevention and early detection in identifying deviations in gait. This pilot study demonstrates the feasibility of using unobtrusive and nonwearable health sensors in addition with machine learning to predict fall risk in older adults by measuring gait. Using anomaly detection with machine learning helps to predict future fall risks in older adults. In-home real-world sensors allow continuous clinical monitoring without requiring constant nursing supervision, supporting the connection of early fall risk and intervention. This study aimed at predicating fall risk to detect anomalies in gait abnormalities within a 10-day window prior to a documented fall. Using depth cameras, passive infrared motion sensors, and bed sensors along with gait characteristics, demonstrated the need for prognostic tools in predicating fall risk. In a nursing perspective, early identification of gait anomalies and fall risks highlight the importance of addressing challenges associated with older adults. Technology assisted monitoring serves as a clinical support tool to enhance communication, nursing assessments, and clinical decision making. Expanding this study to a larger, more diverse population would improve the anomaly detection approach by increasing validation and effectiveness. This foundation can be built upon for future research and testing in improving predictive detection and fall risks.

a. Improve health outcomes and timely interventions for older adults
b. Reduce caregiver burden and help with shortage of residential care while still promoting safety
c. Use of unobtrusive, non-wearable sensors and unsupervised techniques allows for continuous monitoring in deviations.
d. Data suggests that anomaly detection is a valuable prognostic tool for predicting falls.
e. Future studies can focus on expanding its population to validate anomaly detection.

Reference

Farmer, M., & Powell, K. R. (2024). Feasibility of fall-risk detection in older adults: Real-world use of sensor data with machine learning. *Journal of Gerontological Nursing*, *50*(10), 7–10. https://doi.org/10.3928/00989134-20240912-03