Smart Walker: an IMU-Based Device for Patient Activity Logging and Fall Detection

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Hip fractures are common in the geriatric population and represent a growing social and economic burden [1]. They are associated with decreased mobility, and the recovery period can be prolonged. Early mobilization is a critical component of the recovery process. Few studies have quantitatively measured activity levels in patients after hip fracture surgery, resulting in a lack of objective data about mobility status after hospital discharge. Furthermore, each year about 1.5 million elderly people are injured falling, and about 47,300 people aged ≥65 years suffer injuries from falls using walking aids that require an emergency room visit [2]. Patients using walkers are seven times more likely to fall than those that use canes. The risk of repeat falls has been shown to be especially high in patients who have already sustained a hip fracture.

Thus, there is urgent need for a smart device that can detect falls in real-time and alert caregivers and/or emergency assistance. Smart watches and other emerging wearables fill some of this need, but not all users reliably wear them and they do not detect all hazards. Hence, devices that automatically log their use and detect dangers (e.g. falls) can improve patient care and safety.

This research is to build a low cost, smart sensor device that continuously logs patients' mobility data when assistive walking devices are used. Sensor data captured from the walker are analyzed using signal processing and machine learning algorithms. The results provide physicians with more information to assess a patient's progress with recovery and if the patient has met prescribed daily mobility goals.

In this experiment, a wireless IMU was secured using Velcro to the front bar of an orthopedic walker as in Fig. 1. The IMU was the NGIMU [3], which provides motion sensing from the built-in tri-axial gyroscope and tri-axial accelerometer. Data from all 6 channels are sampled at 50 Hz. The NGIMU device communicates directly with a computer through Wi-Fi or Bluetooth wireless links. Data received at the computer can be displayed in real-time and processed by signal processing and machine learning algorithms [4] for motion classification [5].

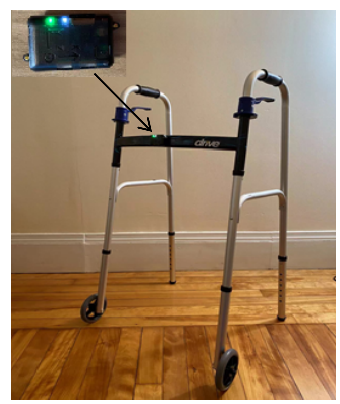

Figure 1. IMU sensor is mounted to the orthopedic walker

Our preliminary investigation reported herein utilized data collected from one subject. The subject provided written informed consent and the experimental procedures were approved by the WPI IRB (Protocol 23-0004). During data collection, each trial lasts 12 seconds of standing, walking, or at most one fall occurred. In the event of fall, a subject holding a walker would lose their grip of the walker and lean forward, causing the walker to abruptly tip over or spin rapidly. After the sudden movement, the walker would remain stationary until the end of the trial. Only one fall event occurred in each trial, and the starting time of the fall in each data collection period was recorded manually. During the walking trial, the subject was instructed to move a step every 3 or 4 seconds, for the simplicity of data labelling. A classification label was assigned for every 100 data samples (2 seconds), as either standing, walking, or falling. A total of 120 trials were conducted, consisting of 30 trials of standing, 60 trials of walking without a fall, and 30 trials that each included a fall. Among the collected data, there were a total of 210 windows labelled as active walking, 30 windows labelled as active falling, and the remaining 480 windows labelled as standing. Additionally, data augmentation was applied to generate more samples of walking and falling by shifting the 2 second original

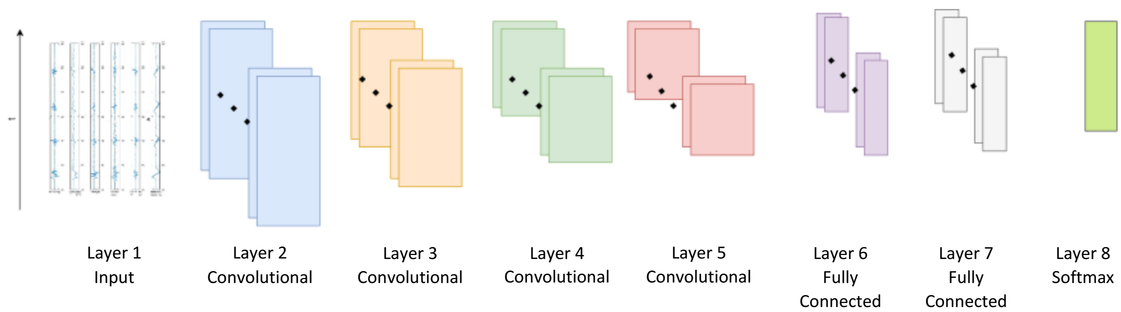

Figure 2. A hybrid deep learning architecture that integrates temporal and spatial context

window left or right by several samples, thus creating a total of 3,030 samples for training the machine learning model.

A six-layered convolutional neural network was trained to classify the data as in Fig. 2. For this preliminary study, no data preprocessing/filtering of the raw input data was conducted. Future work on larger data sets may benefit from doing so. The input of our network is 100 points of 6-axis data captured by the IMU sensor, so the input feature size is 6-by-100. Data are first fed through four convolution layers used for feature extraction. Each layer encompasses 2-D filters for convolution, data pooling, and reLU functions. Data then enter two fully connected layers, which ultimately produce a single classification result. Finally, a softmax layer is used to output the classification results. The CNN was trained in Matlab to perform the task of 3-class classification using a total of 3030 samples. 80% of samples were randomly selected for training and the remaining 20% of samples were used for validation. Five-fold cross-validation was used when training the model.

Table 1. Confusion matrix of the CNN model for multi-class classification

Confusion Matrix	Standing (predicted)	Walking (predicted)	Fall (predicted)
Standing (actual)	35.6%	0.0%	0.0%
Walking (actual)	0.0%	34.7%	0.2%
Fall (actual)	0.0%	0.0%	29.5%

Table 1 shows the confusion matrix of the CNN model prediction results. The overall accuracy is 99.8%. For fall detection, the precision is 99.44%, the recall is 100%. A perfect recall indicates the model did not miss an actual falling, which is of great importance to the users.

A limitation of this preliminary study is the small sample size (one subject) and that all walker falls were similar in orientation (walker tipping in the forward direction, initially) and intensity. A wider subject pool, including walker perturbations in all relevant directions and with varying intensity, is needed as part of future work. And, of course, many patients fall without any perturbation of the walker (fall while reaching toward a surface above the walker). Such falls would not be detected by IMU sensors on the walker.

In summary, this study presents a novel approach of using an IMU device attached to the walker for logging a patient's mobility as well as performing fall detection. Data were collected and labelled for the time windows of walking, falling, and standing. A CNN model was trained for multi-class classification, and cross-validation results showed that the machine learning model achieved a high accuracy. For future work, the data logging as well as machine learning will be moved to the sensor node itself, such that the smart walker device can function normally where wireless networks are not available.

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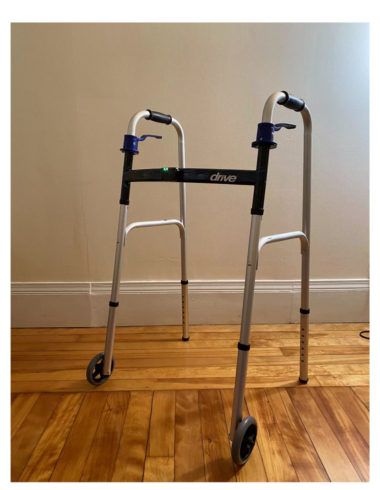
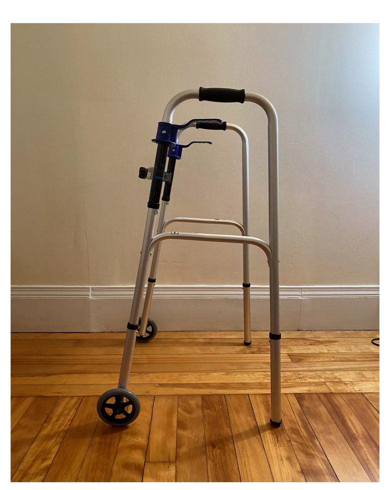
Abstract

- Hip fractures are common in the geriatric population and represent a growing social and economic burden. The risk of repeat falls has been shown to be especially high in patients who have already sustained a hip fracture.
- There is is urgent need for a smart device that can detect falls in real-time and alert caregivers and/or emergency assistance. Smart watches and other emerging wearables fill some of this need but are not reliable at detecting all hazards.
- This research builds a low-cost smart sensor device using an IMU that continuously logs patients' mobility data when assistive walking devices are used. Sensor are analyzed using signal processing and machine learning algorithms through a CNN.
- The results provide physicians with more information to assess a patient's progress with recovery and if the patient has met prescribed daily mobility goals.

Experimental Apparatus

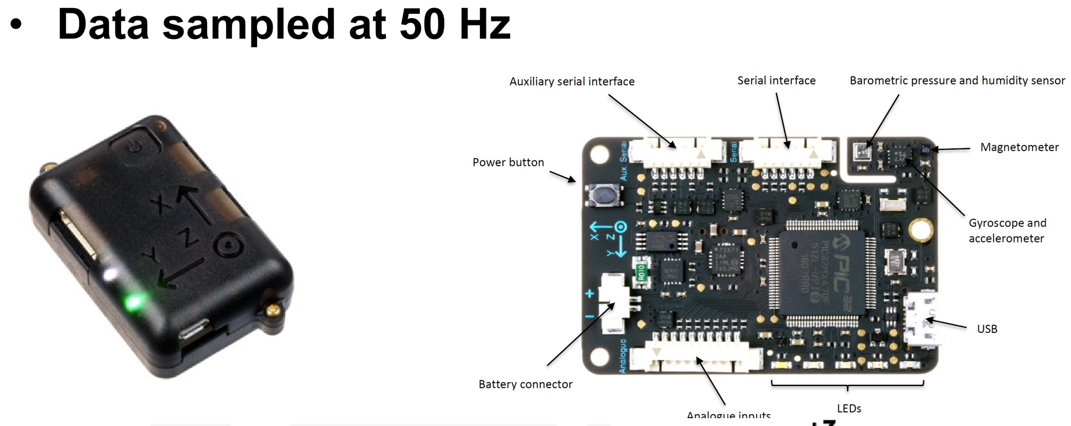
- Drive Medical trigger release folding walker from DeVilbiss Healthcare
- X-IO Technologies NGIMU (general all-purpose IMU)
- IMU secured with vertical-oriented y-axis

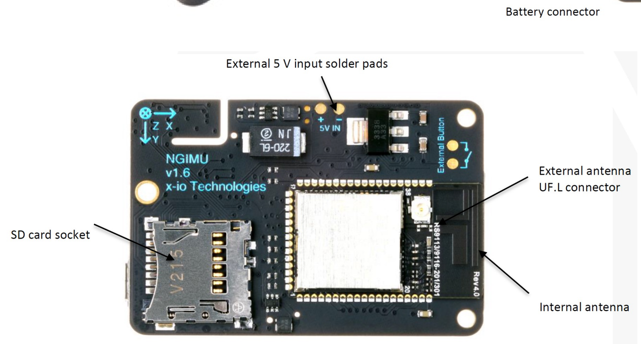


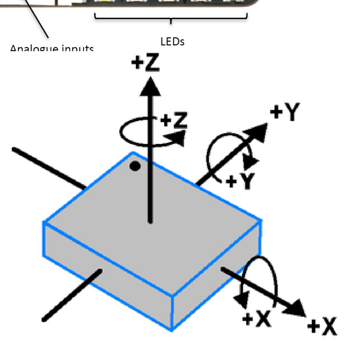


IMU Specifications

- Accelerometer (X, Y, Z)
- Gyroscope (angular rotations Ω_X Ω_Y Ω_Z)
- Magnetometer (not used in this work)
- Wifi/BLE Communication with computer
- Data sampled at 50 Hz







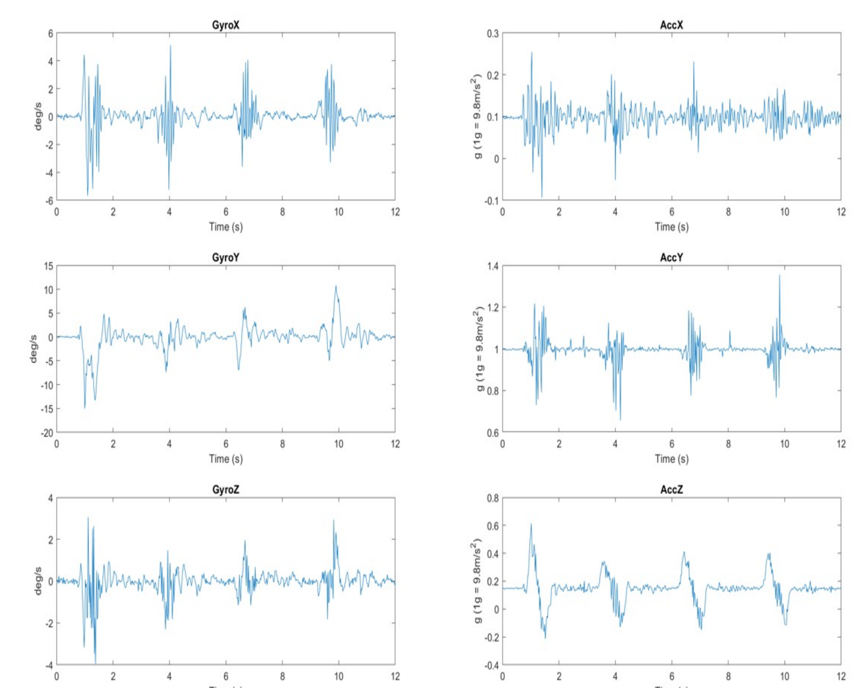
Machine Learning Computing

- Traditional signal processing, e.g. peak detection, works well for detecting the approximated number of steps, but is still not accurate enough for the task of fall detection.
- False-negative fall classification can be life-threatening.
- False positive fall classification would be a major complaint from caregivers.

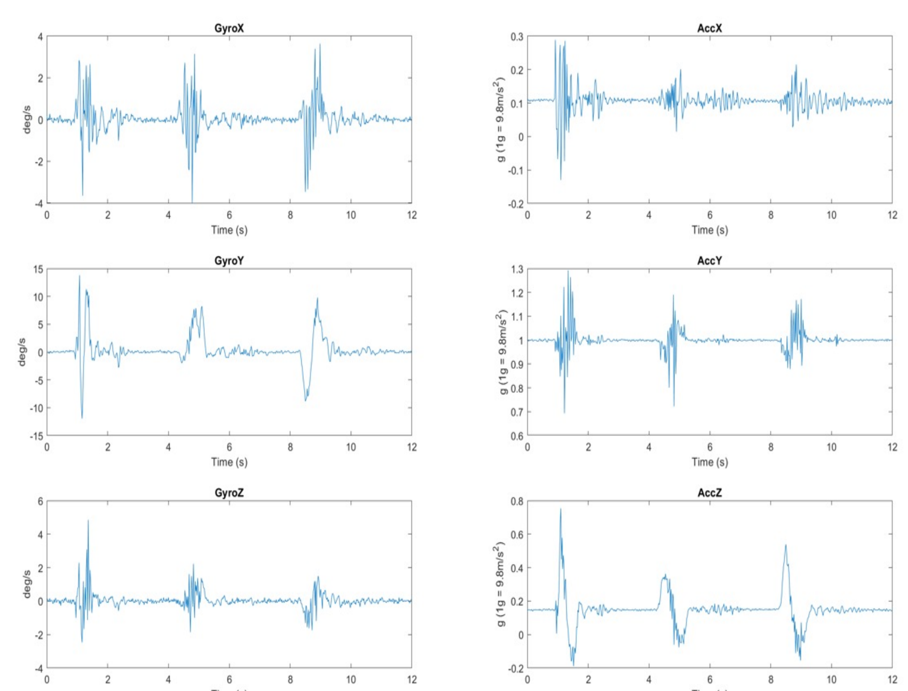
Machine learning provides the necessary accuracy through a dynamic training model.

Experimental Data

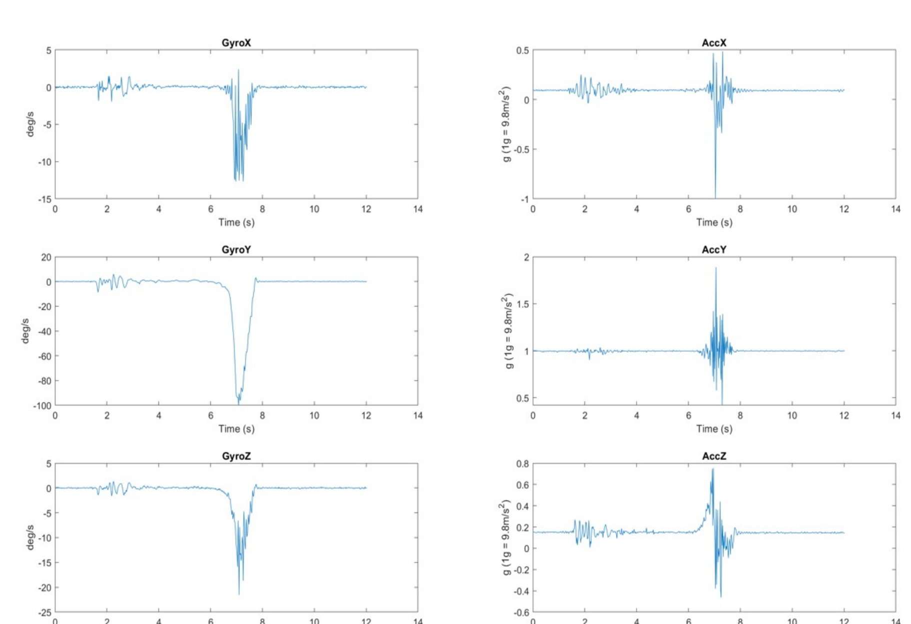
- Trials of 12 seconds
- Walk trials with 3 and 4 steps per trial
- Fall trials with one fall per trial
- Idle trials of continuous sampling



Four-Step Walking Trial



Three-Step Walking Trial



One Fall Event Trial

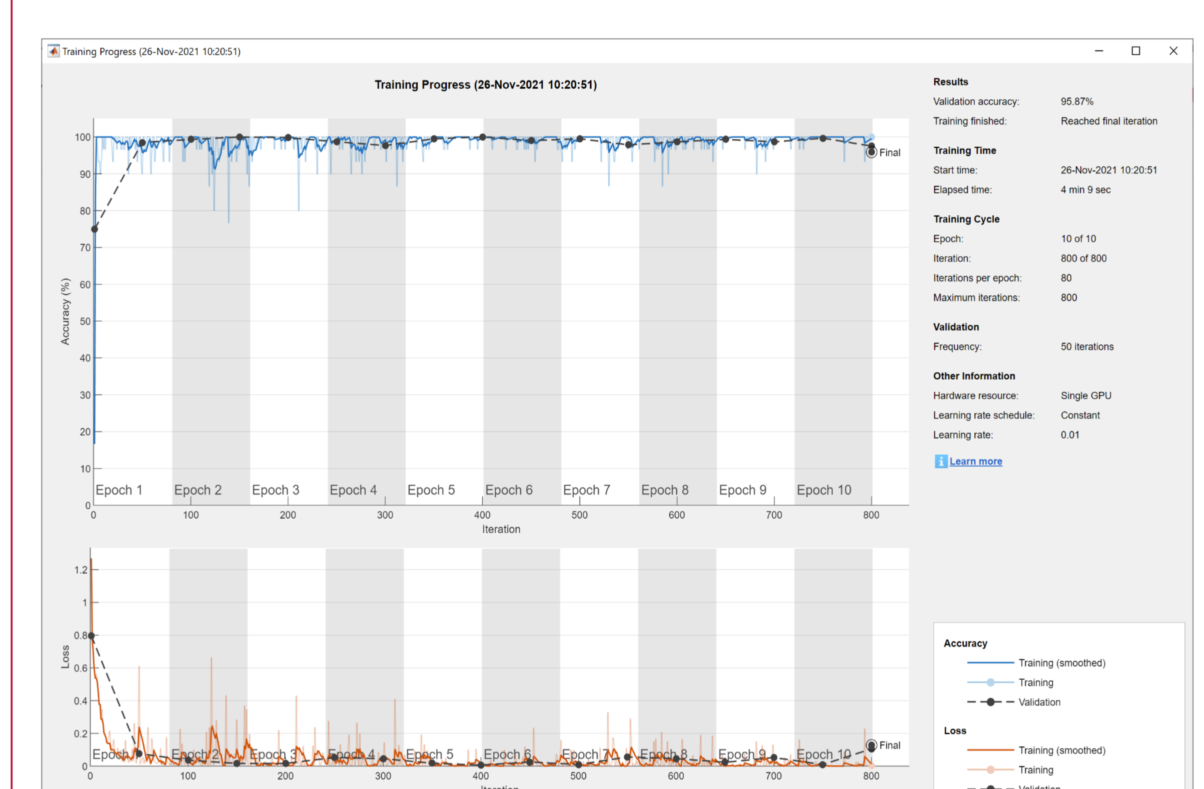
Data Augmentation

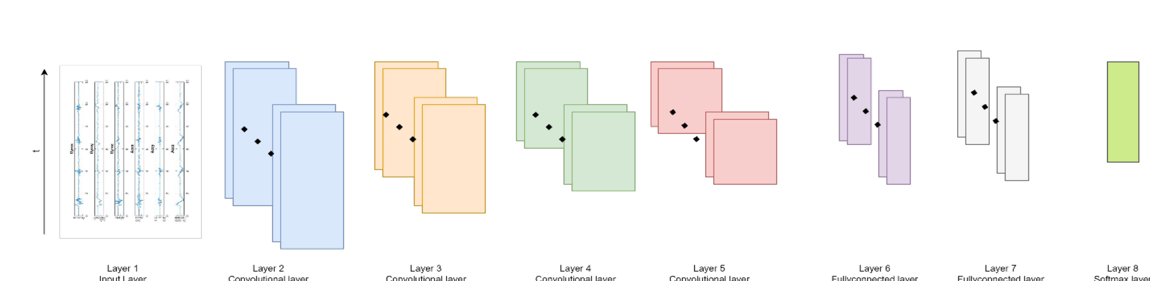
- 12-second trials separated into 2-second windows for classification (100 samples at 50 Hz)
- Windows augmented by shifting slightly to produce more training data and more accurate model
- Walking trials shifted 2 samples to left and right
- Fall trials shifted 1 sample to left 14 times and right 15 times
- Idle trials randomly sampled
- Augments total windows from 240 to 1950 (non-idle)

Categories	Trials	Original Active Windows	Augmented Active Windows	Data Augmentation Method
Walking (3 steps in 12 seconds)	30	30·3 = 90	30·3·5 = 450	Shifting each 2-second active window to the left & right by 2 samples (5x)
Walking (4 steps in 12 seconds)	30	30·4 = 120	30·4·5 = 600	Shifting each 2-second active window to the left & right by 2 samples (5x)
Falling (1 fall in 12 seconds)	30	30	30·30 = 900	Shifting each 2-second active window to the left by 14 & right by 15 samples (30x)
Standing (Not Walking)	30	-	30·36 = 1080	Randomly sample 36 windows by trial (36x)

CNN Model

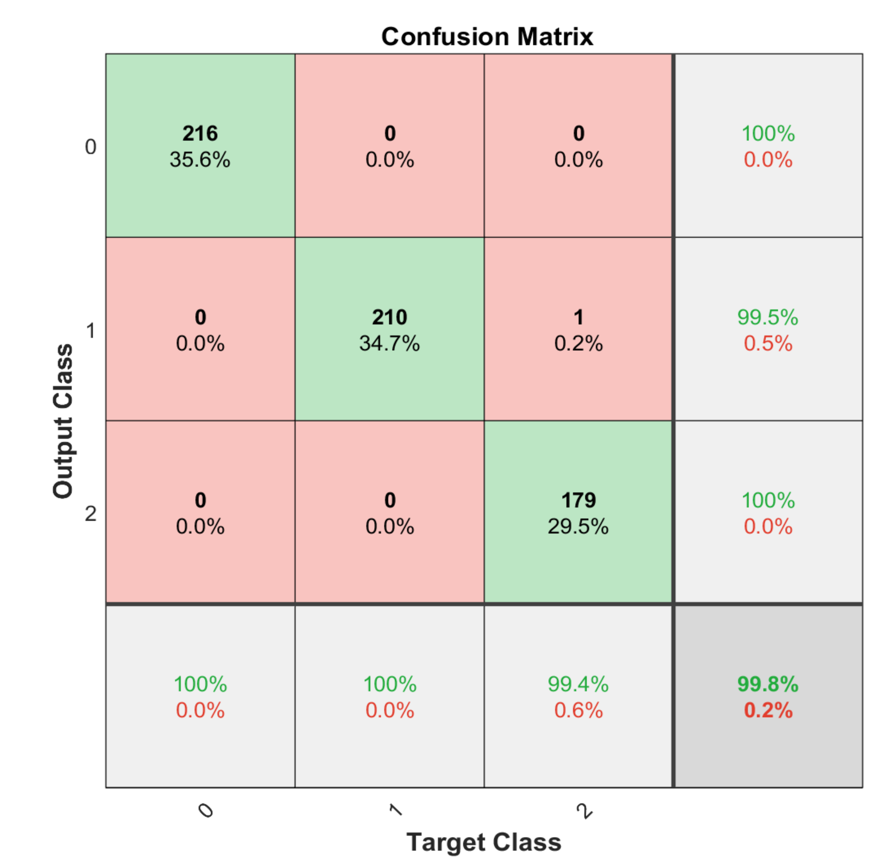
- Input layer
  - 6*100 samples (2 sec*50 Hz)
  - 3-axis accelerations (X, Y, Z) & 3-axis rotations (Ω_X, Ω_Y, Ω_Z)
- 6-layer convolutional neural network (CNN)
  - 4 convolutional layers (Convolution, ReLU/nonlinearity, pooling)
  - 2 fully connected layers
- Output layers
  - 3-class classification results (0: standing, 1: walking, 2: falling)





Classification Results

- Total of 3030 labelled samples: 80% used for training and 20% used for validation (randomly split; repeatable)
- We reduce the likelihood of missing the fall event by applying 50% overlap for consecutive 2-second time windows (A fall missed is likely detected in the next time window.)
- Model is trained for 10 epochs but converges quickly
- For 606 validation samples, overall classification accuracy is 99.8%.
- Only 1 classification error: 1 sample of fall is mis-classified as walking



Summary/Conclusion

- In summary, this study presents a novel and economical approach to fall detection using an IMU device attached to the walker for mobility tracking.
- 3030 windows of augmented data were collected and labelled for the classifications of of walking, falling, and standing.
- A CNN model was trained for multi-class classification, and cross-validation results showed that the machine learning model achieved a high accuracy that is repeatable.
- For future work, the data logging as well as machine learning is planned to be implemented directly onto the IMU onboard processor, so that the sensor can communicate without the intervention of a computer or Wi-Fi.