PROJECT ARTEMIS

Group: 9785-19, Data Mining for Modelling and Prediction of falls by the Elderly

University Of Canberra - ITS Capstone Project 2021 S2

Kurt Pattison, Mitch Durbin, Riley Rumble, Vithuran Jeyasingham

PROJECT SPONSOR: Dr Masoud Mohammadian

Abstract

Project Artemis' aim is to contribute to the development of wearable fall detection technology.
Falls represent a serious risk to elderly people, which can be mitigated through use of such technology and fall-detection algorithms. In developing such an algorithm, the primary need is to differentiate between falls and daily activities.
Project Artemis uses a Neural Decision Tree through the Keras Deep Learning API to identify falls within the simulated dataset to 100% training and validation accuracy. Further testing indicated that problematic and over-simulated datasets are a significant issue in the development of accurate fall detection software.

Background

Falls present a major and ongoing health concern for elderly members of our society. According to the Australian and New Zealand Falls Prevention Society [2], approximately 30% of adults over 65 suffer from at least one fall per year. This figure had increased by 2% for women, and 3% for men since 2008 [3], which is a positive indication that fall-related injuries will only increase with Australia's aging population.

Falls are particularly common in the elderly community due to changes in the body caused by aging that make walking and balancing more difficult. The most common fall-related injuries are hip fractures, wrist fractures, head injuries and thigh injuries - all of which carry a risk of long-term damage. With falls increasing, so too has the number of falls resulting in head damage which has doubled over the past 10 years [4].

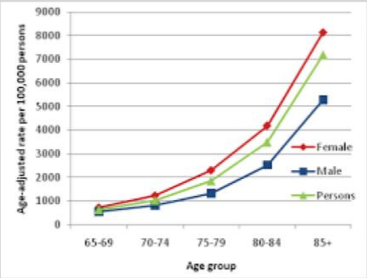


Figure 1: Fall-related injury hospitalisations, males females and persons 65 years and over by age, NSW, 2009-10 [5]

The severity of these injuries is particularly worrying when considering that approximately 85% of falls occur within the home [3], and that 51% of people aged over 85 live alone [4]. These statistics highlight the need for fall-detection technology to mitigate the risk of an elderly fall-sufferer being left alone.

In addition to the personal risk is the financial toll that fall injuries present. In 2014, the estimated cost of fall-related care for older Australians was $600 million [7]. Without preventative action, this figure is expected to exceed $1.37 billion by 2051.

Fall-detection technology can be expected to decrease the potential severity of falls and the associated costs by ensuring elderly falls are detected and treated as soon as they occur.

Figure 2: Graphic of Statistics around elderly falling rates [6]

Introduction

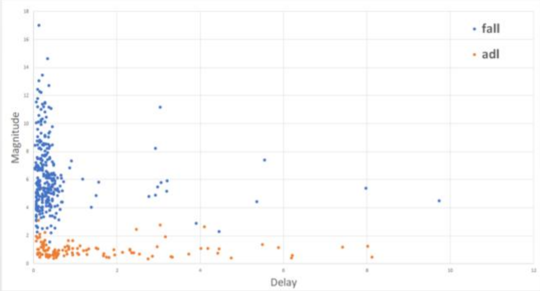
The purpose of Project Artemis is to contribute towards the development of wearable fall detection technology by modelling collected fall data [1], with emphasis on differentiating between falls and activities of daily living (ADL). This model will be tested for accuracy, fine-tuned to improve detection accuracy, and optimized for future smartwatch capability. Note: A proof-of-concept for smartwatch capability is out-of-scope for this project.

Methodology & Materials

All modelling stages of this project, from importing data to model testing, were conducted using Spyder IDE - an open-source IDE for scientific programming in the Python programming language.

The initial phase of the project was a review of current literature on the topic of fall detection algorithms. The focus of this phase is to determine the suitability of using either a traditional threshold-based modelling technique, or an artificial intelligence modelling technique. The techniques were considered in the context of modelling accelerometer based fall detection data, as supplied in [1].

First, the data was read from a CSV file into a dataframe to plot the time and acceleration on a line graph. Following this, the two values of interest, magnitude and delay, were extracted. The magnitude being the difference between the minimum and maximum values for the Signal Vector Magnitude (SVM) measured in Gs. The delay being the time difference between the minimum and maximum values for the SVM.



Due to the need to differentiate between falls and ADL, the most suitable predictive modelling technique is a classification based supervised machine learning model.

Amongst current fall detection research, there is a noticeable lack of standardisation between the collection methodologies used. Real-world datasets are also extremely scarce. Due to this, a back-up modelling technique was selected, however implementation was not required. Due to the highly skewed nature of the dataset, blanched accuracy is the most meaningful indicator of a model's usefulness.

The primary modelling technique chosen was a Neural Decision Tree. This is due to clearly defined rules and intelligible distribution of observations; making the Neural Decision Tree easily understood by humans. It also exists as a middle ground between traditional threshold-based approaches and more modern AI modelling.

The Keras deep learning API and associated TensorFlow library provided the neural network library necessary for applying the Neural Decision Tree. The Keras API was chosen due to the available Neural Decision Tree being robust and easily implemented.

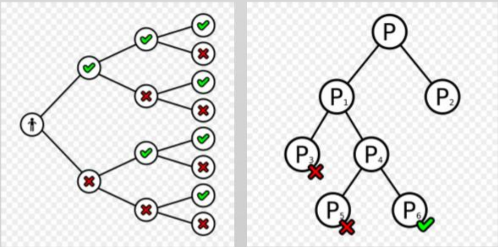


Figure 3 & 4. A graphic representation of the structure of a decision tree

A decision tree modelling script was produced in Python by adapting the source-code from *KERAS GUIDE*. In total, 60 experiments were run, varying the random seed, percentage of dataset used for validation, maximum depth of the decision tree and number of epochs.

Results

Through 57 of the 60 experiments applied to the dataset, the decision tree achieved 100% accuracy for differentiating between falls and ADL. This result was only affected when the depth of the tree was set to 1 and the train accuracy dropped to a low of 0.6127.

100% train accuracy often indicates model overfitting, where a statistical model fits too closely against the training data. While the results indicate the model could be sensitive to over training, the delineation in results following the depth decrease is an indication that the dataset used was overly simulated.

Accelerometer-based fall detection data is scarce, and the dataset used was too simulated to represent lifelike falls. This may have created a larger differential in the movements between falling and ADL than what actually exists in real life.

Conclusion

Over the course of this project, only one dataset was used. As seen in the results, we achieved 100% accuracy in all of our runs. This is more than likely an indicator that our data, like the data used by others in this field, is too simulated after feature extraction.

Future fall detection projects should endeavour to collect and test on more lifelike data - such as data from sensors after a real fall has occurred. Further modelling techniques may also be applied to the same dataset to prove it being problematic.

The feature extraction method used could prove suitable for future fall detection technology development.

References

[1] Cotechini, V., Belli, A., Palma, L., Morettini, M., Burattini, L. and Pierleoni, P., 2019. A dataset for the development and optimization of fall detection algorithms based on wearable sensors. *Data in Brief*, 23, p.103839.

[2]Anzfallsprevention.org. 2021. *Info about falls | Australian and New Zealand Falls Prevention Society*. [online] Available at: <https://www.anzfallsprevention.org/info/> [Accessed 20 September 2021].

[3] NewsGP. 2021. *Falls the cause of 75% of injury hospitalisations for older people*. [online] Available at: <https://www1.racgp.org.au/newsgp/clinical/falls-the-cause-of-three-quarters-of-all-hospitali> [Accessed 20 September 2021].

[4] Australian Institute of Health and Welfare. 2021. *More older Australians hospitalised for fall-related head injuries - Australian Institute of Health and Welfare*. [online] Available at: <https://www.aihw.gov.au/news-media/media-releases/2019/september/more-older-australians-hospitalised-for-fall-relat> [Accessed 23 September 2021].

[5] NSW Department of Health. 2021. *Falls Health Statistics: Falls Among Older People*. [PDF]. Available at: <http://www.healthstats.nsw.gov.au/resources/falls_health_statistics_r.pdf> [Accessed 23 September 2021].

[6] Gold Age Australia. 2021. *PREVENTING FALLS IN THE ELDERLY - Gold Age Australia*. [online] Available at: <https://goldage.com.au/preventing-falls-elderly/> [Accessed 30 September 2021].

[7] Public Health Association Australia. 2021. *Policy-at-a-glance – Fall Injury Prevention in Older People Policy*. [online] Available at: <https://www.workingwitholderpeople.edu.au/documents/fall-injury-prevention.pdf> [Accessed 23 September 2021].