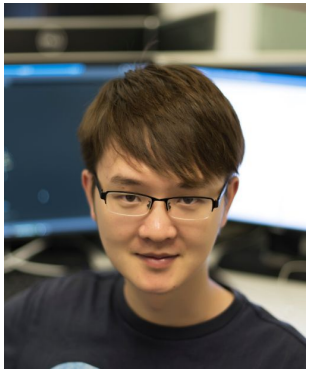
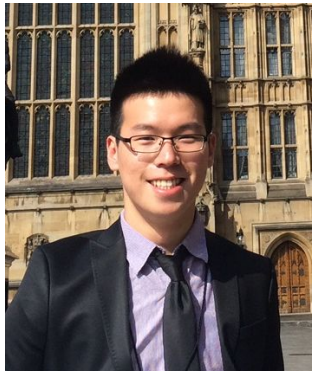
RF-Based Fall Monitoring Using Convolutional Neural Networks



Yonglong Tian*

Guang-He Lee*

Hao He*



Chen-Yu Hsu

Dina Katabi

* equal contribution

In US, about three-fourths of deaths due to falls occur in the 13% of the population age ≥65

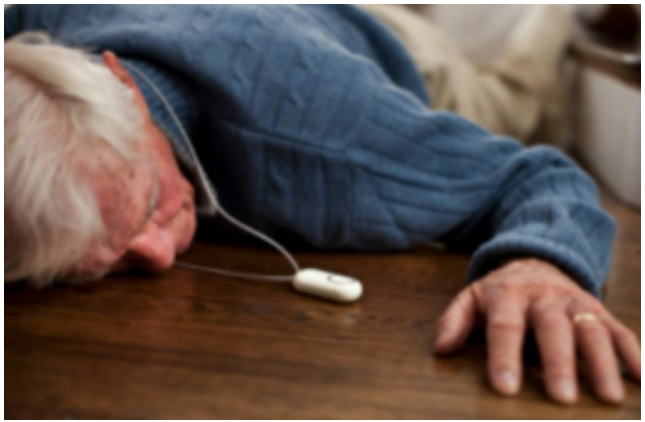
One in three adults over the age of 65 experiences a fall each year; 12 million seniors in the US live alone

Falls result in $34B of direct medical costs annually

Sources: (1) Falls in older people: epidemiology, risk factors and strategies for prevention. *Age and ageing.* (2) *John Hopkins Newsletters.*

Current solutions

Wearables devices



- Forget to wear or charge the devices
- Recently an elderly woman got strangled with her fall detection pendent.

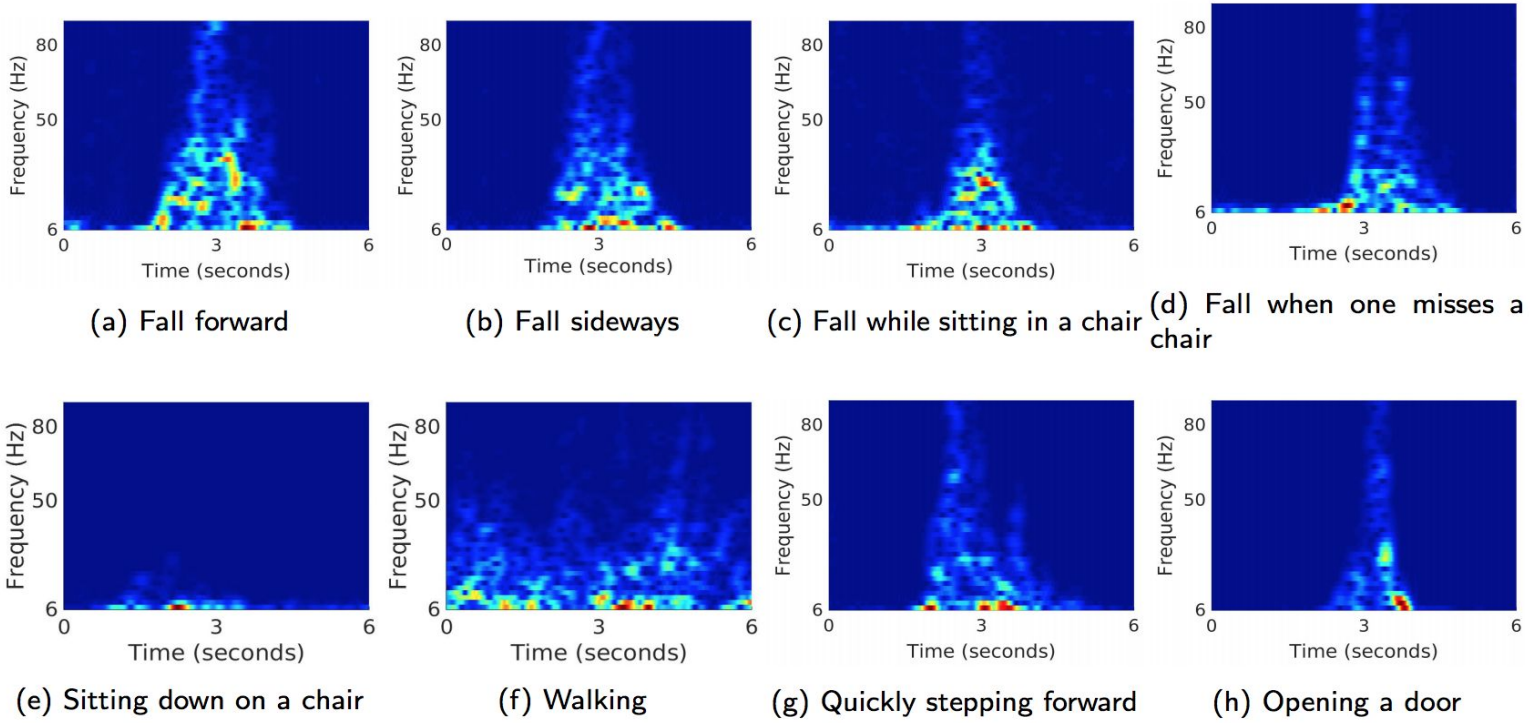
Non-wearable

Privacy Issues. Suffer from occlusion

Not easy to generalize to new environments.

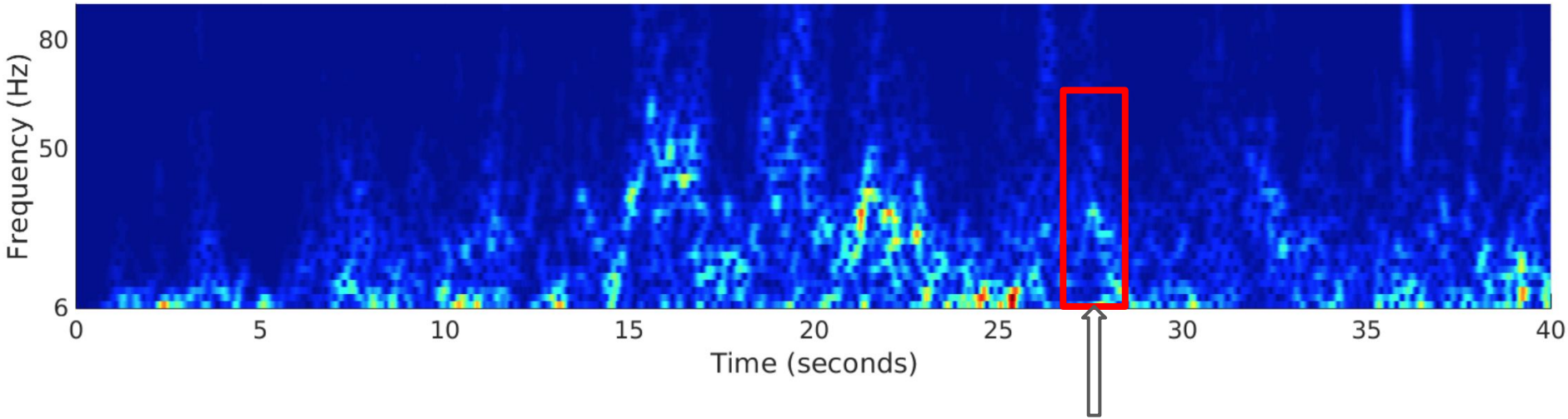
Issues of wireless fall detection (Doppler/CSI-based)

Fails to distinguish between falls and other motion patterns



Issues of wireless fall detection (Doppler/CSI-based)

Fails to detect falls when other motion exists



Fall happens, but is overwhelmed by another walking people

Issues of wireless fall detection (Doppler/CSI-based)

Fails to generalize in new environment and people

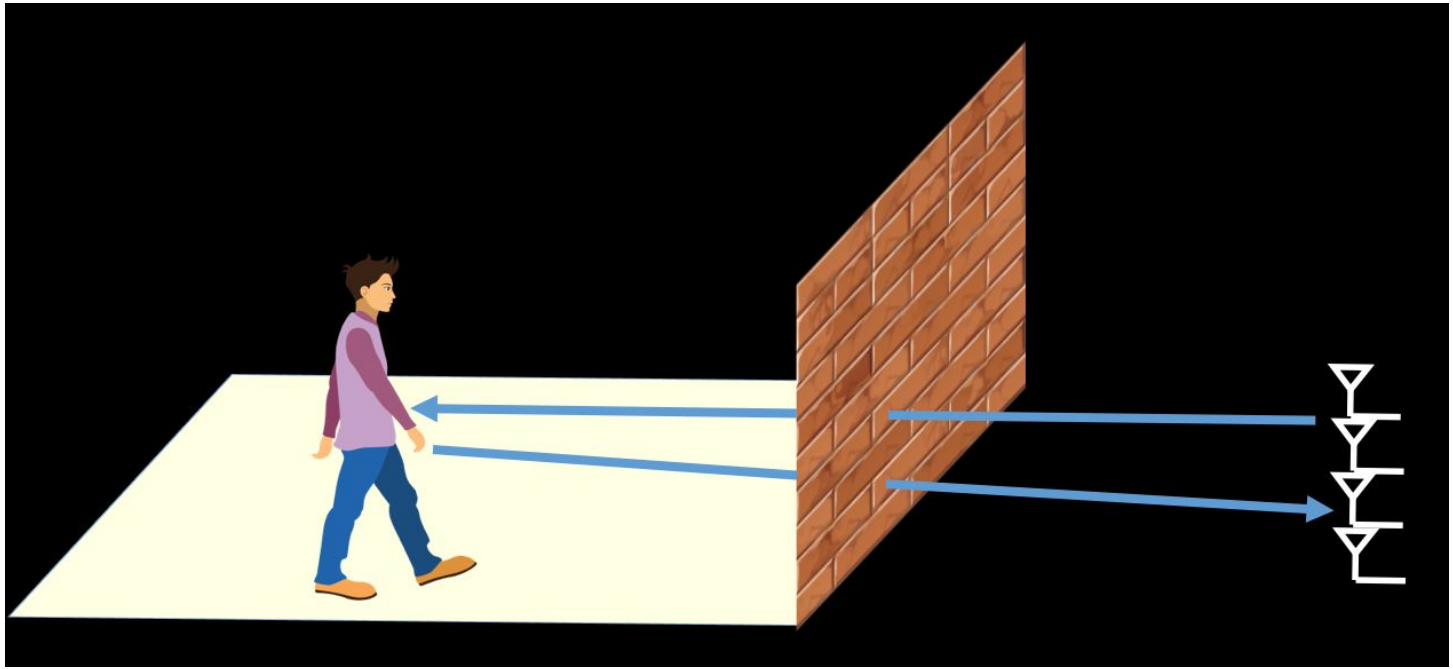
Training set

Testing set

Aryokee

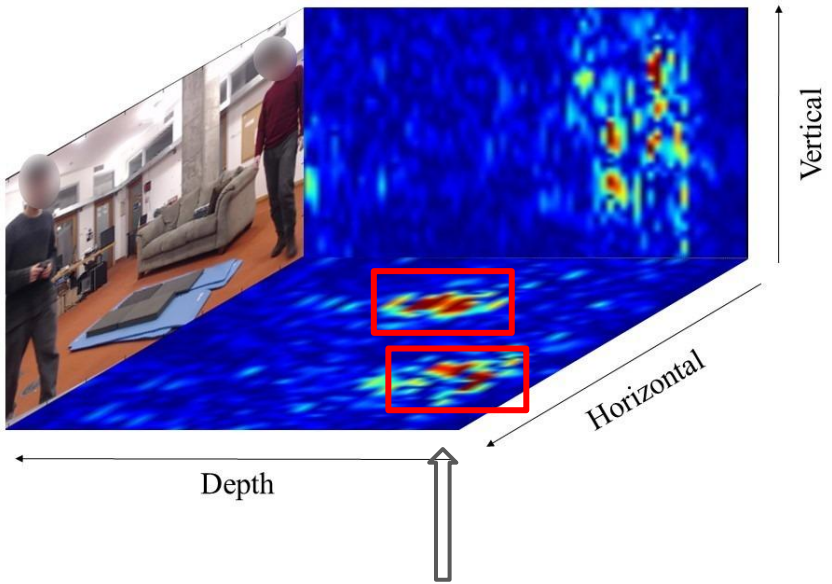
- Aryokee is highly accurate when generalizing to unseen environments and people.
- Proposed cascaded convolutional model beats previous models, such as Linear SVM, Kernel SVM and LSTM, by a large margin.
- Extensive experiment on dataset that contains more than 20 hours data: including 145 people and 57 environments

FMCW radio waves with antenna array

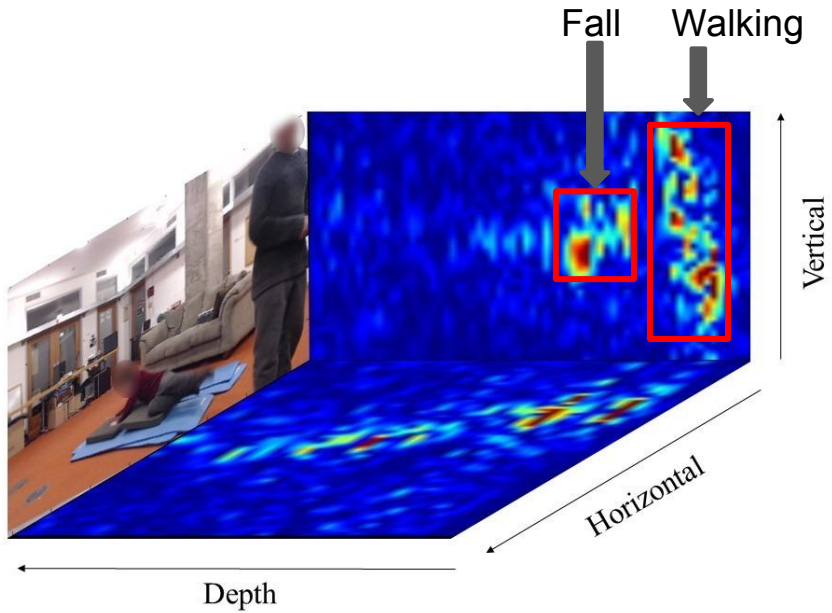


Traverse time → Distance
Multiple antennas → Angles

How the signals look like?

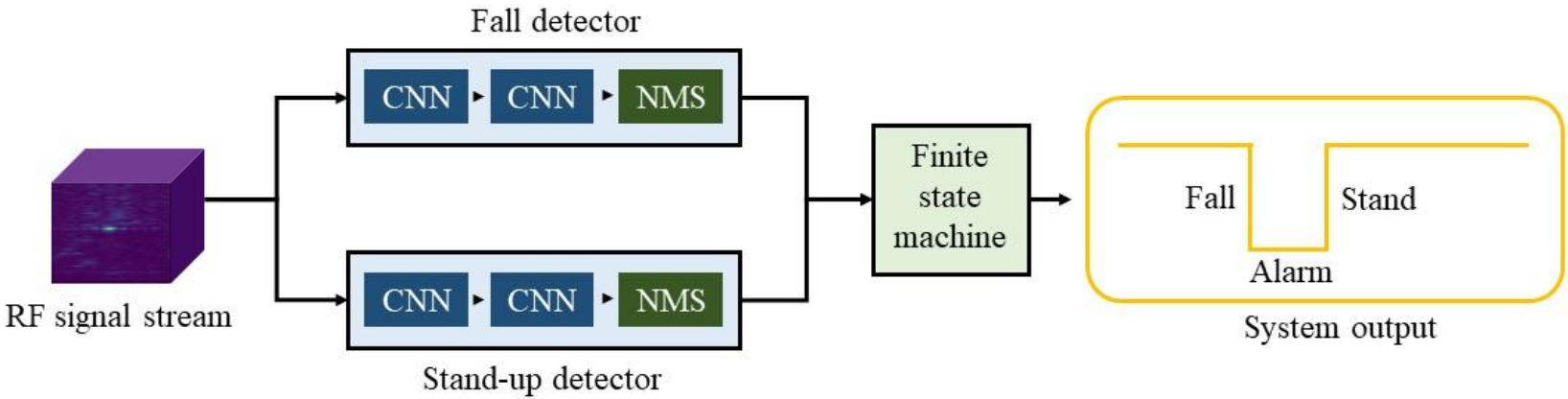


Two people are spatially separated

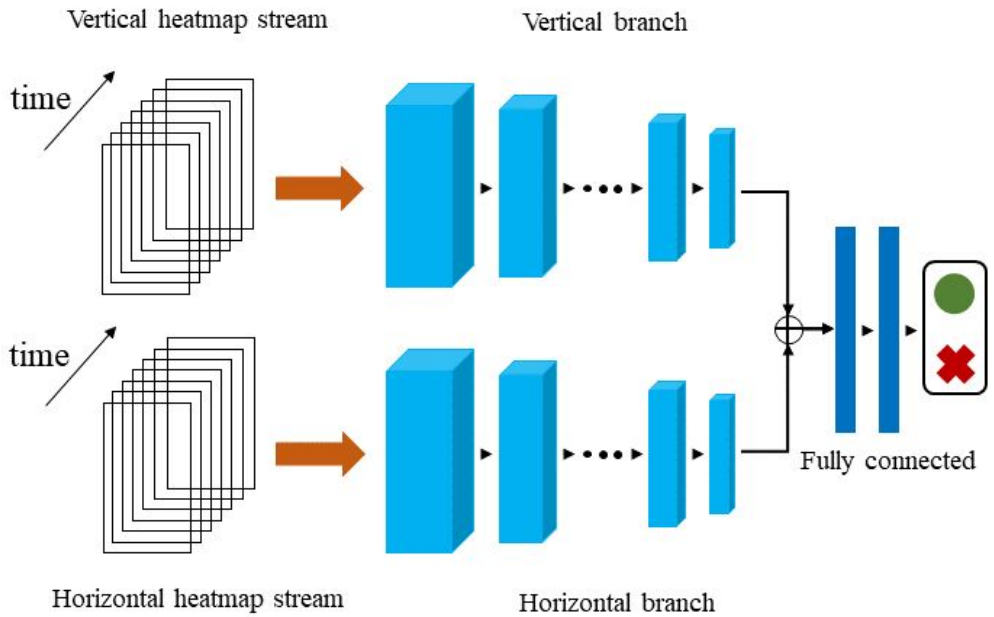


Fall and walking are separated

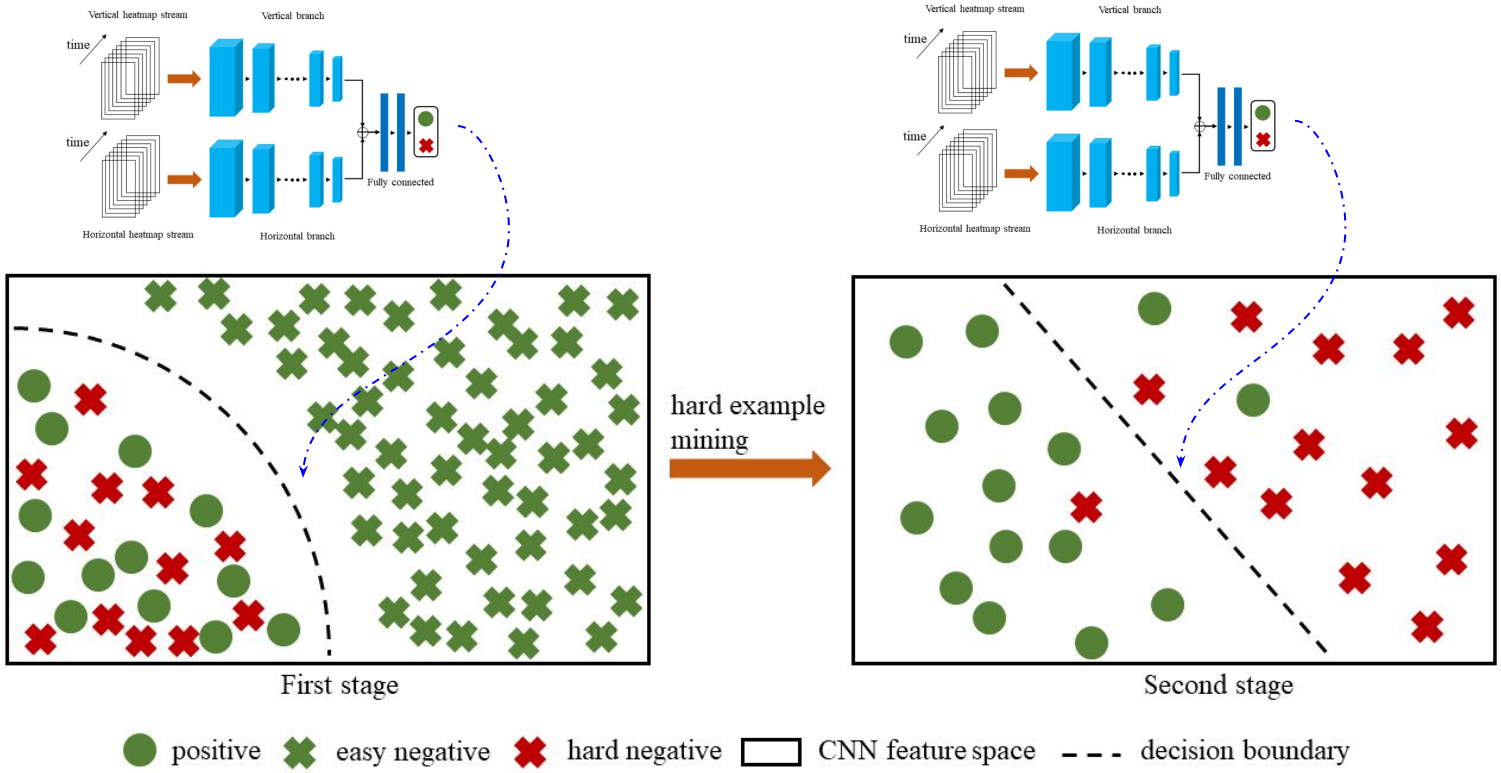
Aryokee Model Overview



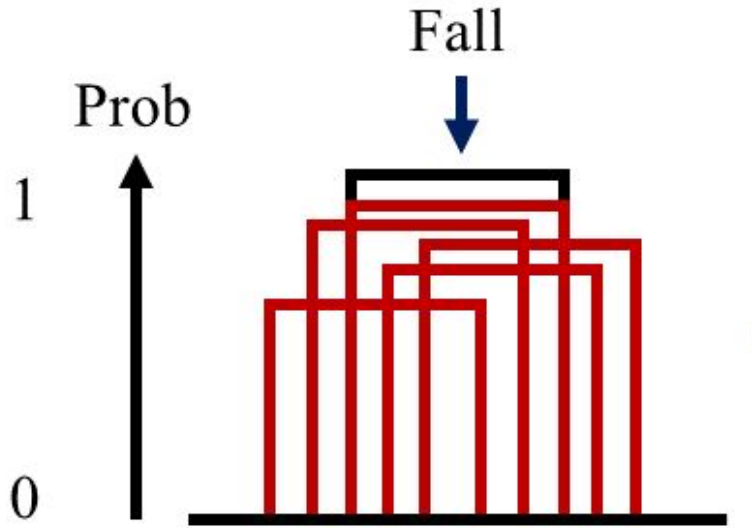
Challenge: how to fuse the information from the horizontal and vertical heatmaps
Solution: CNN model with two branches applying fusion in feature space



Challenge: extreme unbalanced positive and negative samples
Solution: multi-stage dectection via cascading classifiers



Challenge: duplicate detection results around a single fall
Solution: non-maximum suppression delivers single but accurate detection result.



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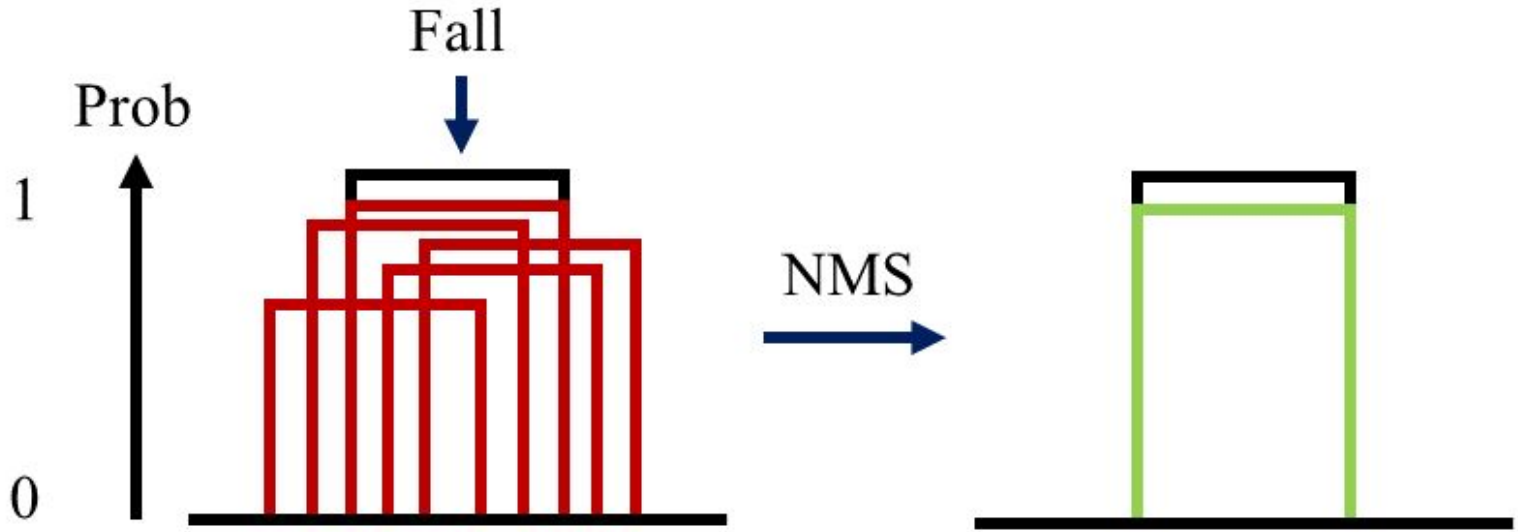
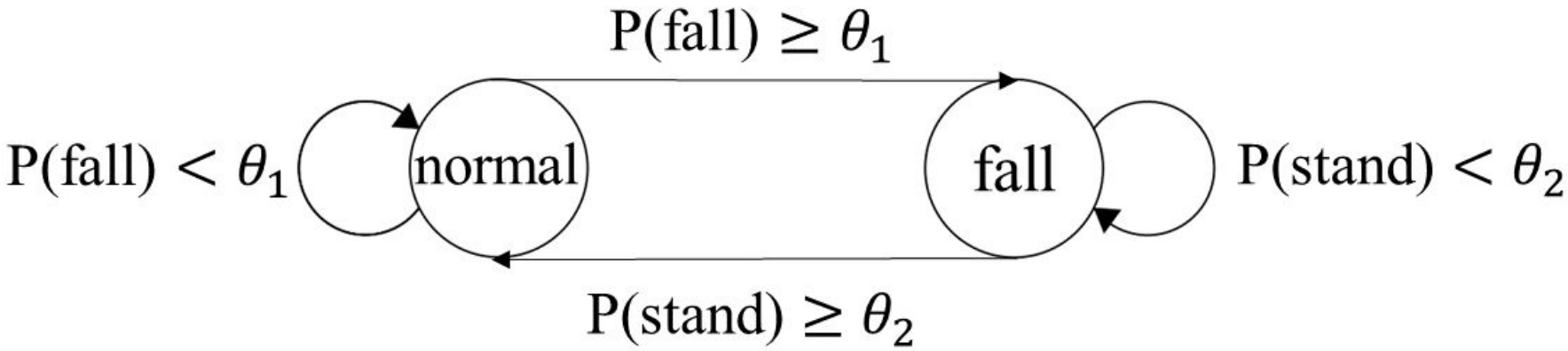


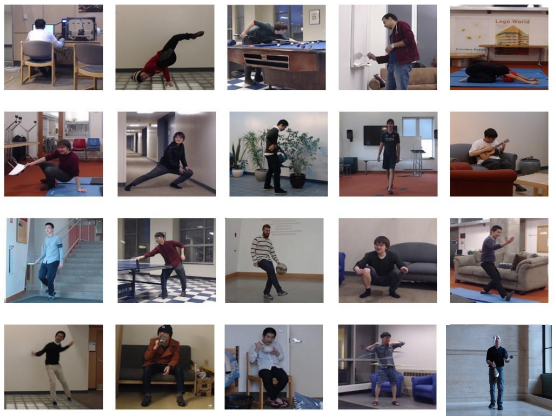
Challenge: how to continuously know the current state of the target person?
Solution: extra standup detector and state machine.



Evaluation (dataset)

Table 1. Dataset statistics and comparison with past work.

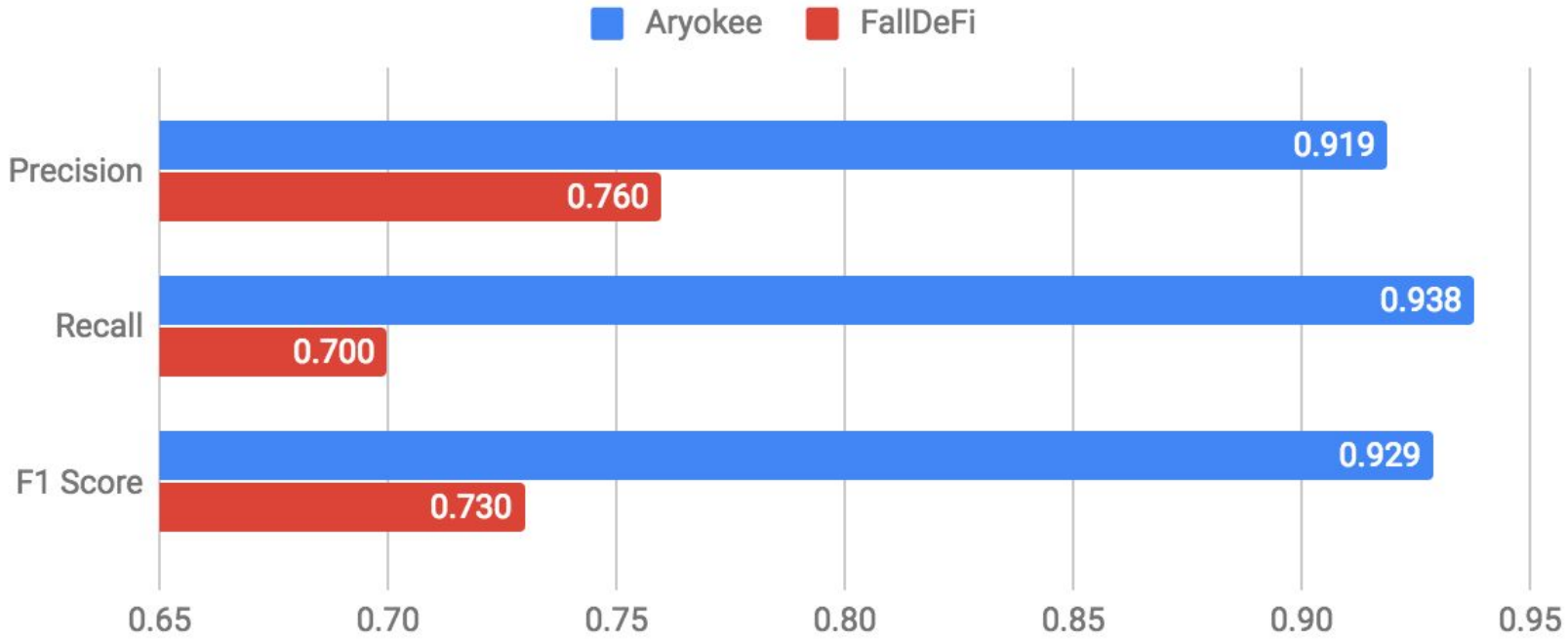
	number of falls	number of non-falls	number of fall patterns	number of non-fall patterns	number of people	number of environments
Ours dataset	541	550,000	18	40	145	57
Palipana *et al.* [41]	326	744	4	8	3	5
Jokanović *et al.* [25]	117	291	4 (different angles)	3	3	2



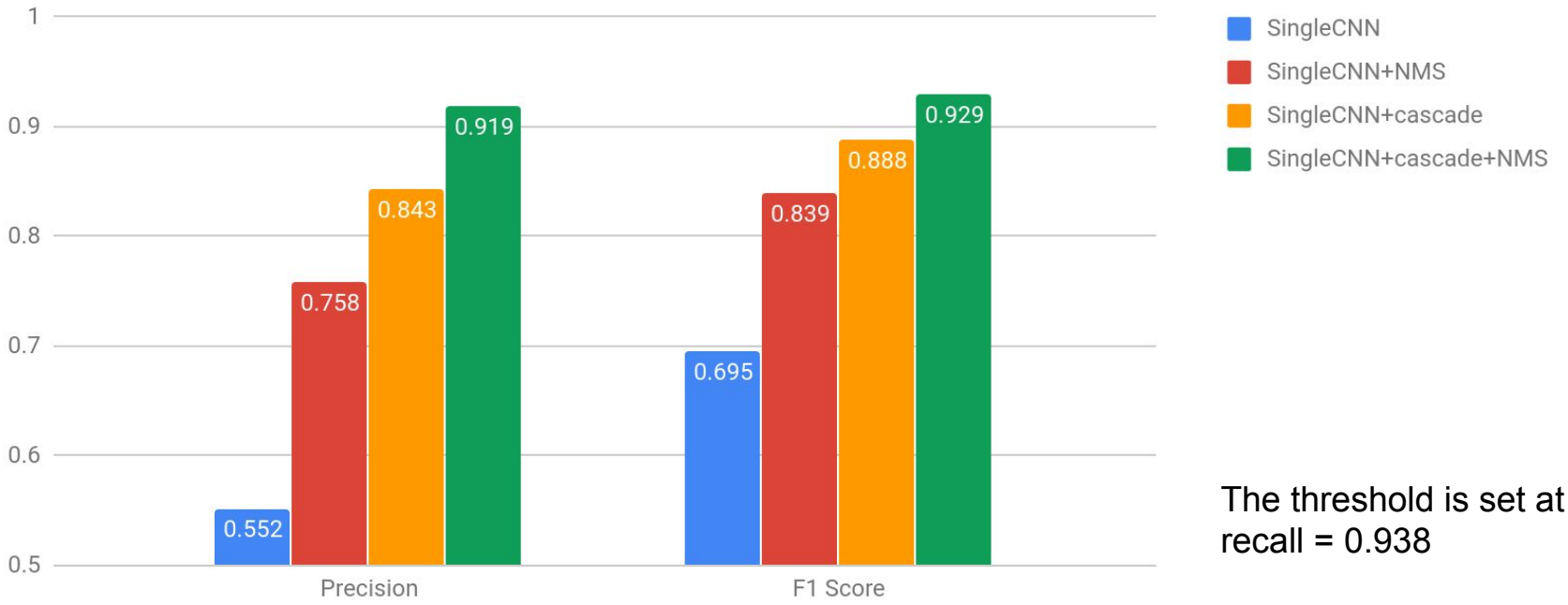
Non-Falls

Falls

Evaluation (main results)

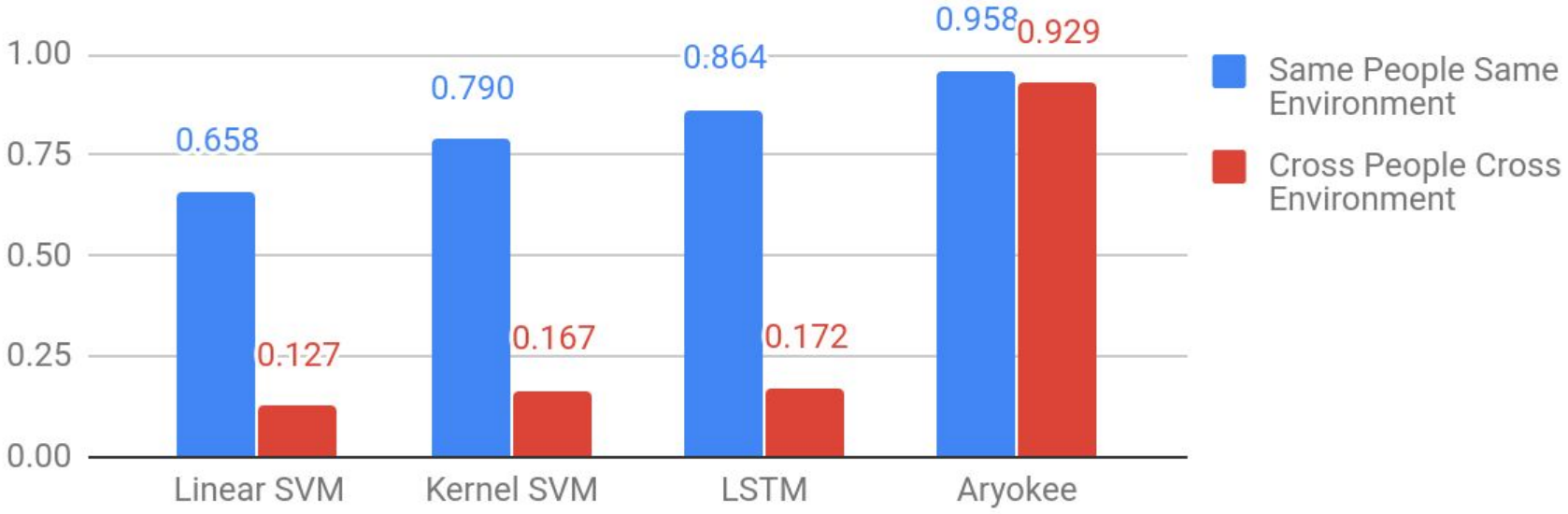


Evaluation (model ablation)



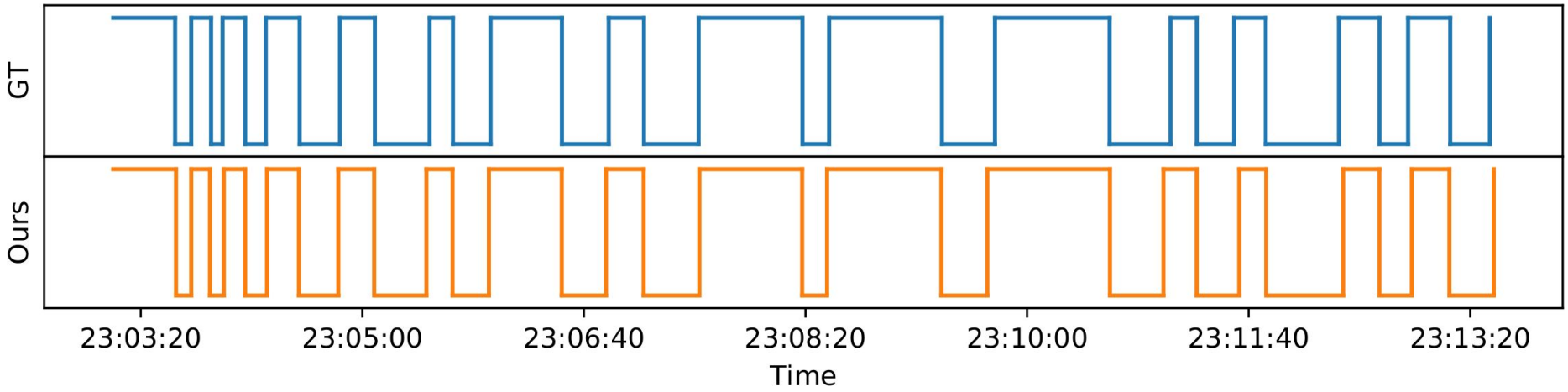
The threshold is set at recall = 0.938

Evaluation (comparison with baseline models)



F1 Score Results

Evaluation (state monitoring)



Conclusion

1. An accurate fall detection system
   a. Convolutional Nets
   b. Cascaded model
   c. NMS

2. A multi-functional design for continuous state monitoring

3. Rich empirical study
   a. vs. prior art
   b. vs. classic ML models
   c. ablation study

Thanks Q&A