

# Detecting Falls and Slips in Wheelchair Users Using Low-Resolution Thermal Imaging

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## **Aging Society and Privacy Concerns**

Monitoring individuals in private rooms while protecting privacy is essential.



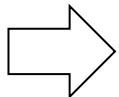
## **Falls of wheelchair users**

Falls are a major cause of fatal injuries especially wheelchair user.



## **Caregiver Workload & Non-Urgent Slips**

- Monitoring nursing home rooms heavily burdens caregivers.
- Misclassifying slips as falls increases caregiver workload and risks overlooking real dangers.



**Fall detection system with protecting privacy.**

# DEVICE CANDIDATES

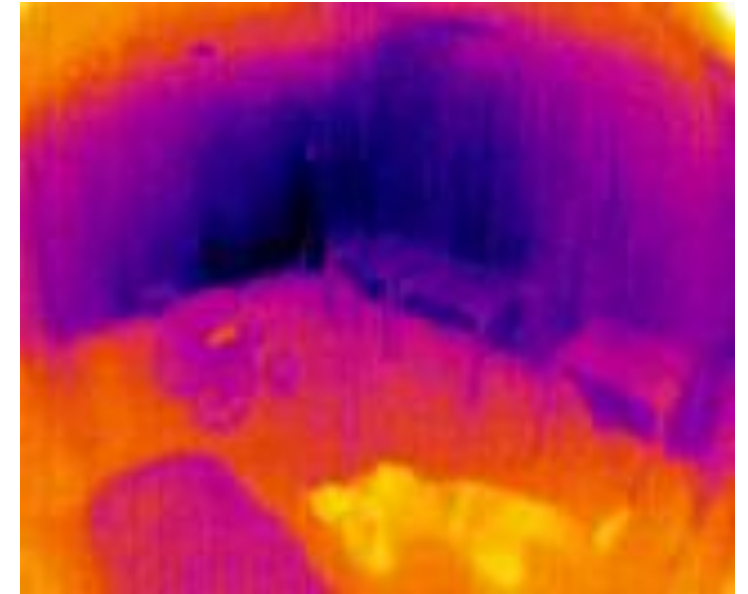
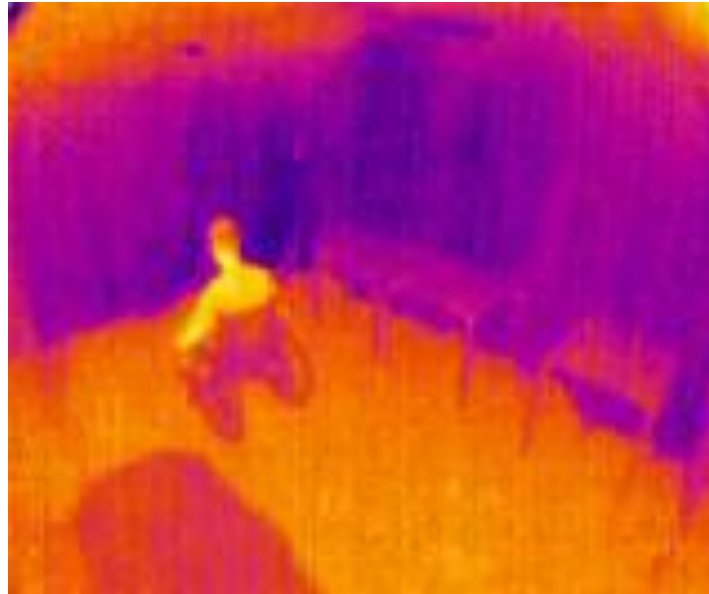
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	Privacy	Non-invasive	Easy of use	Affordability	Accuracy
<b>Wearable sensor</b>	✓	✗	✗	✓	✓
<b>Wi-Fi UWB</b>	✓	✓	✗	✓	✗
<b>RGB camera</b>	✗	✓	✓	✓	✓
<b>3D LiDAR</b>	✓	✓	✓	✗	✗
<b>Depth camera</b>	✓	✓	✓	✓	✗
<b>Thermal camera</b>	✓	✓	✓	✓	?

- Existing video-based fall detection using CNNs.
- CNNs struggle to extract features from thermal images

## Thermal images

- ✓ Lack of fine textures
- ✓ Rough silhouettes
- ✓ Blurry body parts
- ✓ Temperature noise

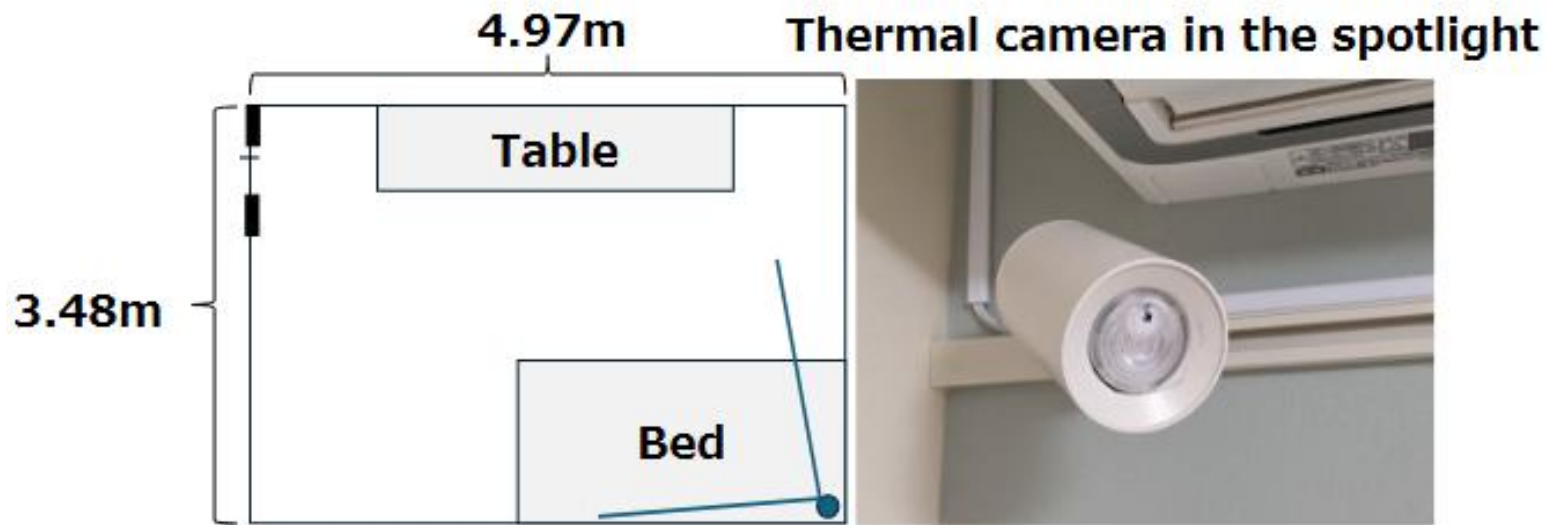


**Fall Detection using CNN and Torso Features (FDCTF)**

# DATA COLLECTION

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- Simulated private room environment.
- 10 to 30 seconds videos, fixed camera angle, one person
  - 39 fall events
  - 45 slip events
  - 23 daily activity videos



Simulated room layout and thermal sensor placement



Captured original image

## Preprocessing

Emphasize the human figure

## Getting features using YOLO

Bboxes & posture probabilities from YOLOv8

## Image Features Extraction

Getting torso features (Torso Angle Change)

## Frame Level Prediction using LSTM

Frame → 'usual', 'under falling' or 'after falling'

## Event Level Prediction

Event → 'caution' or 'emergency'

## Preprocessing



Original image



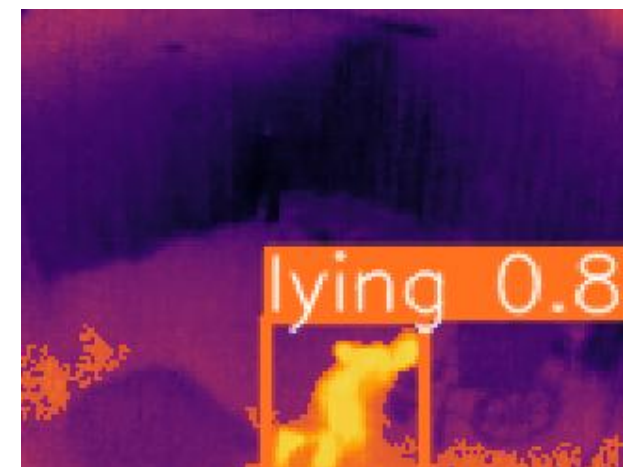
Enhancing human image

## Training of YOLO model

- Detect person positions in images
- Output posture class probabilities: Sitting, Lying, Standing
- Train the model using the created dataset



Sitting & Head



Lying

# Torso Angle Changes

Preprocessing

Getting features  
using YOLO

Image Features  
Extraction

Frame Level Pred-  
iction using LSTM

Event Level  
Prediction

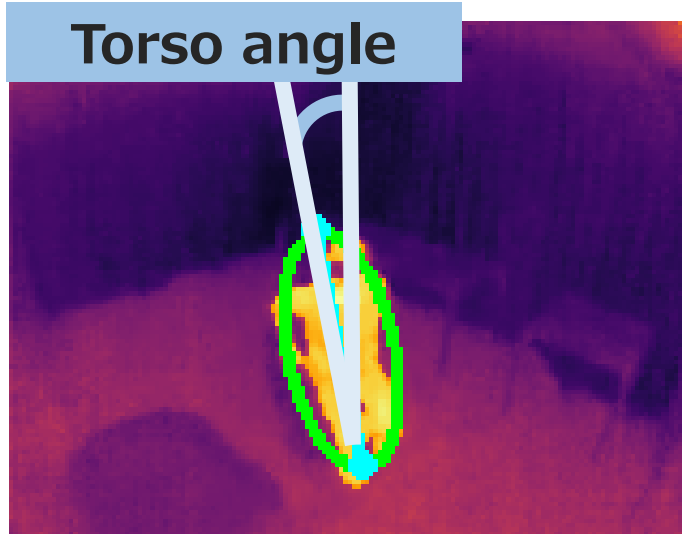
7

## Crop and Binarize images



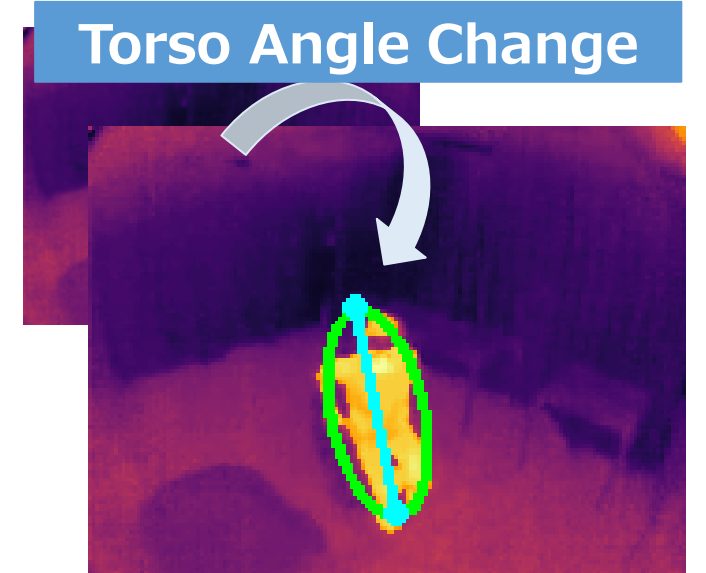
For better feature extraction using the bboxes.

## Extract Torso Angle



An ellipse is fitted to the silhouette

## Calculate Torso Angle Change



Absolute difference in tilt angles



# Other Torso features

Preprocessing

Getting features  
using YOLO

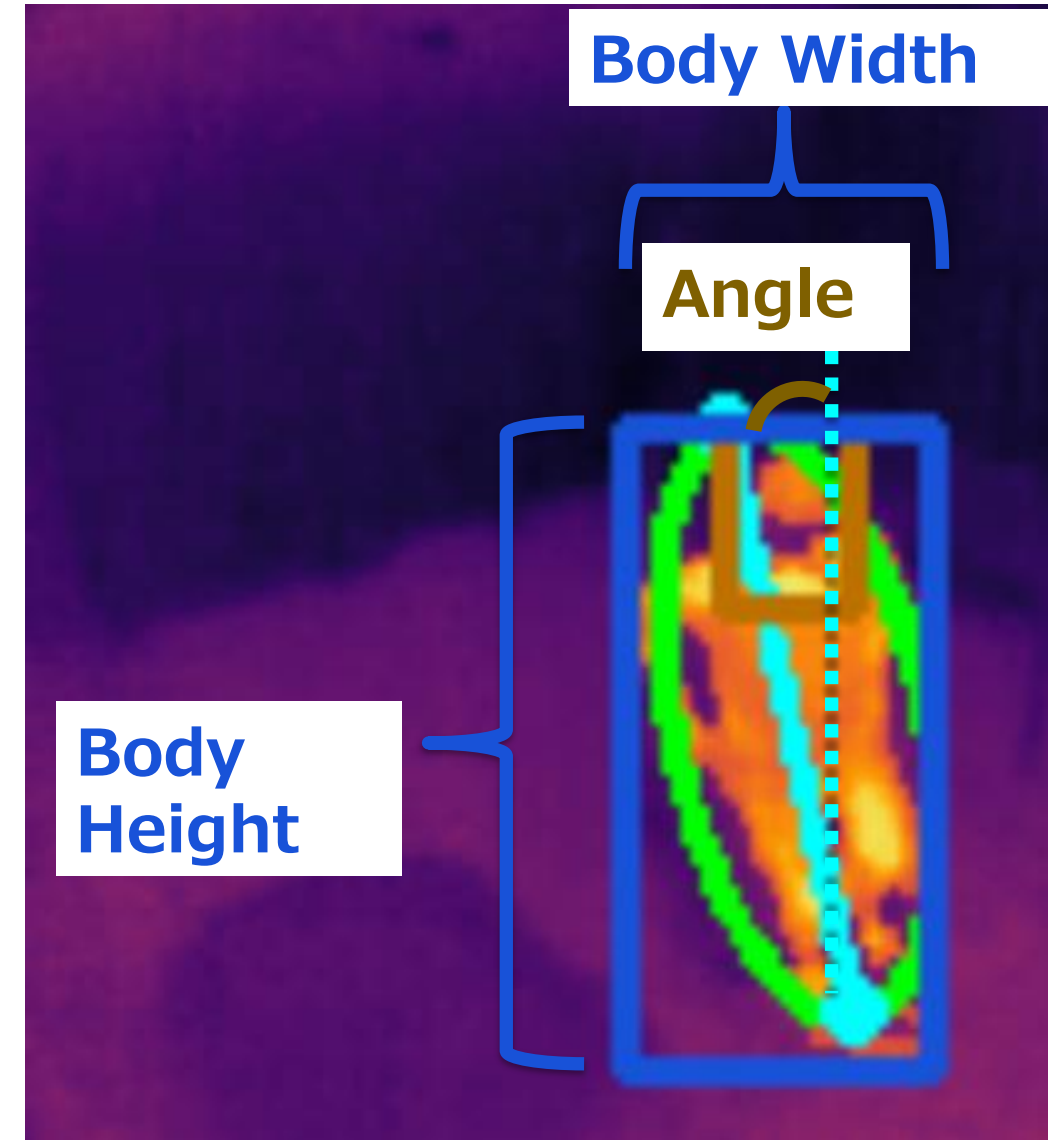
Image Features  
Extraction

Frame Level Pred-  
iction using LSTM

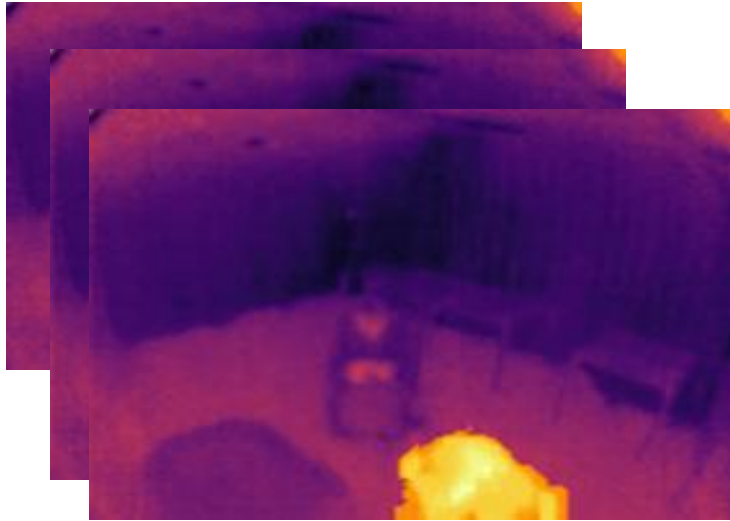
Event Level  
Prediction

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Feature type	Feature	Abbreviation
Torso Features	Torso Speed	TS
	Head Z-coordinate	Z
CNN Features	CNN Feature Vector	CFV
	Posture Probabilities	PP



Split video into  
4-second



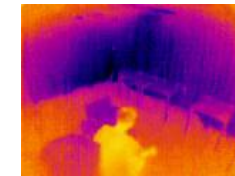
4-second video

Model

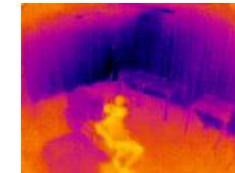
**LSTM**

Input: CNN &  
Torso feature

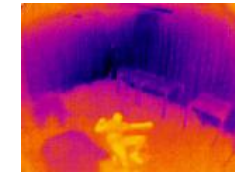
Prediction  
classification



'usual'



'under falling'



'after falling'

**final frame label**

# Definition of TP/FN

Preprocessing

Getting features  
using YOLO

Image Features  
Extraction

Frame Level Pred-  
iction using LSTM

Event Level  
Prediction

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1. 'after falling' frames (  $C$  ) exceeding  $C_{max} \rightarrow$  'Pred Event.'
2. Differences( $D$ ) between the start frames ( $D_{max} = 5$ -seconds)
3.  $D < D_{max} \rightarrow$  TP,  $D \geq D_{max} \rightarrow$  FN

## Actual event1

Ground truth	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
Frame level prediction	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1

**Pred event1**

$D=5$   $C=8$

# Caution / Emergency

Preprocessing

Getting features  
using YOLO

Image Features  
Extraction

Frame Level Pred-  
iction using LSTM

Event Level  
Prediction

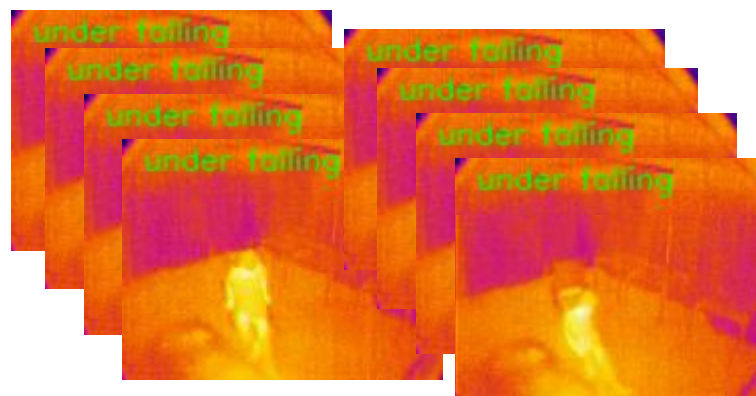
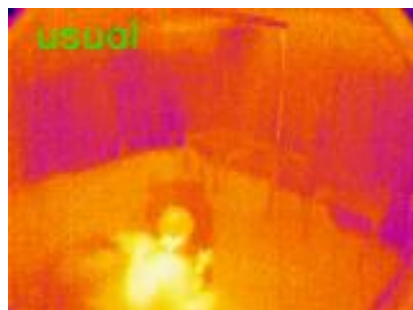
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Start frame

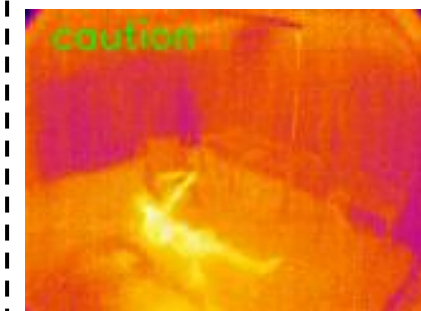
'under falling' sequence

end frame

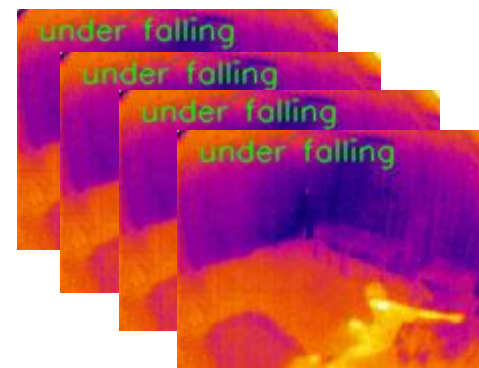
caution



'under falling' frames  $>$  (Th = 2seconds)



emergency



'under falling' frames  $\leq$  (Th = 2seconds)



# Single Environments Results

- CFV(raw images)  
>CFV(thermal image)
- FDCTF method  
> only CNN-based features
- CFV + PP +TAC is highest combination

LSTM input features		F1
CNN Features only	CFV (from raw images)	0.56
	CFV (from binarized thermal image)	0.67
	CFV+PP	0.91
FDCTF	CFV+PP+TAC	1.00
	CFV+PP+Z	0.95
	CFV+PP+TS	0.96

# Multi Environments Results

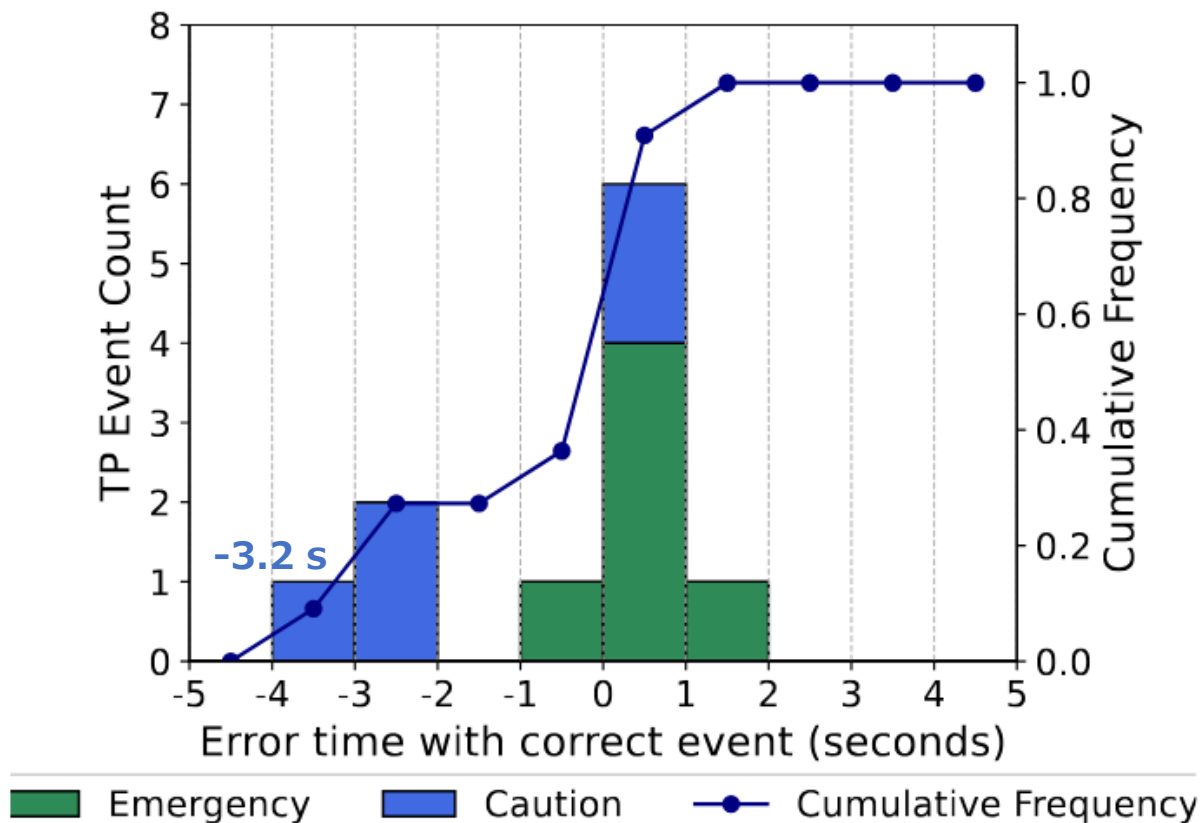
- CFV(raw images)  
>CFV(thermal image)
- FDCTF method  
> only CNN-based features
- CFV + PP +TAC  
is highest  
combination

LSTM input features		F1
CNN Features only	CFV	0.56
	CFV+PP	0.67
FDCTF	CFV+PP+TAC CFV+PP+TAC +Multi(acc, tilt)	<b>1.00</b>
	CFV+PP+TAC +Multi(acc, tilt)	0.95
	CFV+PP +Multi(acc, tilt)	0.96

# CFV+PP+TAC RESULTS

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- CFV+PP+TAC: F1 score of 1.0 ( $\leq 3.2s$ )
- 5.2 FPS (CPU i7-9700K) , 8 FPS (GPU RTX 2070)



(a) to (c) = 'emergency', (d) to (f) = 'caution'.



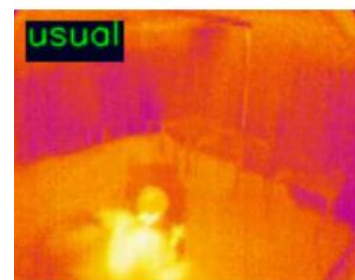
(a) Usual sitting on a wheelchair



(b) Under falling 1 second



(c) Emergency (high-risk fall)



(d) Usual on a bed



(e) Under falling 7 seconds



(f) Caution (low-risk slip)



**Emergency Fall  
Detected**



**Caution Fall  
Detected**

## Conclusion

- FDCTF combines CNN and torso features to improve accuracy.
- FDCTF meets requirements.
  - Privacy, Non-invasive, Ease of use, Affordable, Accuracy
  - Realtime running

## Future work

Enhanced robustness in various environments:

- Different camera positions and angles
- Diverse individuals

# Appendix

**Emergency Fall  
Detected**

**Others**