LapseNet: A Hybrid CNN-LSTM Approach for Accurate and Efficient Vision-Based Fall Detection

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Agenda

1. Background
2. Related Work
3. Methods
4. Results & Discussion
5. Conclusion
6. Future Work

Background

Background

- Falls are the leading cause of injury for adults ages 65 years and older[1]
- 37% of the 14 million US adults who experienced a fall required medical attention from 2012 to 2018[2]
- 50% of falls among individuals aged 70+ resulting in injuries needing medical treatment[3]

[1] Centers for Disease Control and Prevention. National Center for Health Statistics. National Vital Statistics System, Mortality 1999–2021 on CDC WONDER Online Database. Published May 9, 2024.

[2] Centers for Disease Control and Prevention. Older Adult Falls Data. Older Adult Fall Prevention. Published May 9, 2024.

[3] Vaishya R, Vaish A. Falls in older adults are serious. Indian J Orthop. 2020;54(1):69-74. Published 2020.

Related Work

Related Work

- Wearable devices
  - Hussain et al.[4] - F1 score of 0.67
  - Limitations: sensitivity to stress-induced movements and impact with an object
- Sound-based approaches
  - Kaur et al.[5] - Accuracy of 0.867
  - Limitations: privacy concerns and noisy environments
- Biomedical systems
  - Butt et al.[6] - Accuracy of 96.5%
  - Limitations: lacks testing on target demographic and has an insufficient number of trials
- Vision-based technology
  - Maitre et al.[7] - Best accuracy of 89%
  - Show promise, but currently lags behind other technologies

[4] Hussain F, Sheng QZ, Zhang W, et al. Activity-aware fall detection and recognition based on wearable sensors. IEEE Sens J. 2019;19(12):1. Published February 2019.
[5] Kaur P, Mishra S, Patel P, et al. Fall detection from audios with audio transformers. Smart Health. 2022;26:100340. Published August 23, 2022.
[6] Butt FS, La Blunda L, Wagner MF, Schäfer J, Medina-Bulo I, Gómez-Ullate D. "Fall Detection from Electrocardiogram (ECG) Signals and Classification by Deep Transfer Learning." Information. 2021; 12(2):63. Published 2021.
[7] Maitre J, Bouchard K. Fall detection with UWB radars and CNN-LSTM architecture. J Biomed Health Inform. 2006;25(4):1-11. Published October 2020.

Methods

Data Acquisition

- Four diverse public datasets:
  - UR Fall Detection
  - Multiple Cameras Fall
  - CAUCAFall
  - UBFC Fall Detection

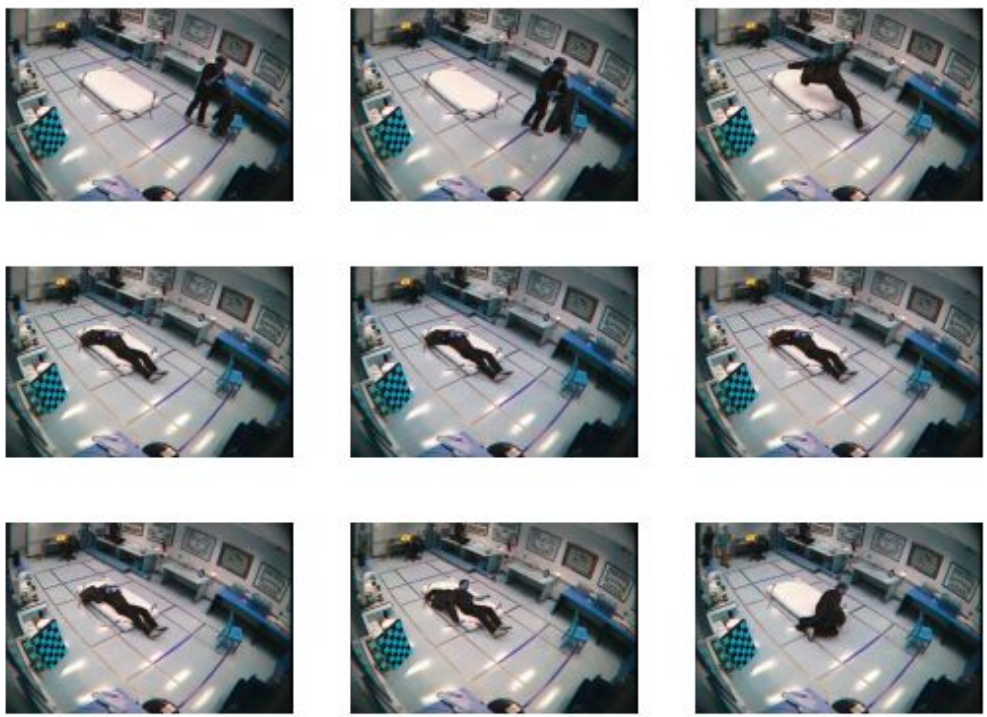

Fig. 1. Sample video frames from CAUCAFall Dataset

Preprocessing

- CAUCAFall, Multiple Cameras Fall, and UBFC datasets consist of files in .avi format
- UR Fall Detection Dataset stores videos as folders of frames (PNGs)
- Processed into lists of images of size 128 × 128
- Condensed videos into sequences of 30 frames
- Created and concatenated datasets
  - tf.data.Dataset object
  - from_tensor_slices method
- Batch size of 16

CNN-LSTM Model

- Hybrid CNN and LSTM
- Keras & Tensorflow backend
- Trained to minimize binary cross-entropy loss

$$\mathcal{L}_{\text{BCE}} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(p_i) + (1-y_i)\log(1-p_i)\right]$$

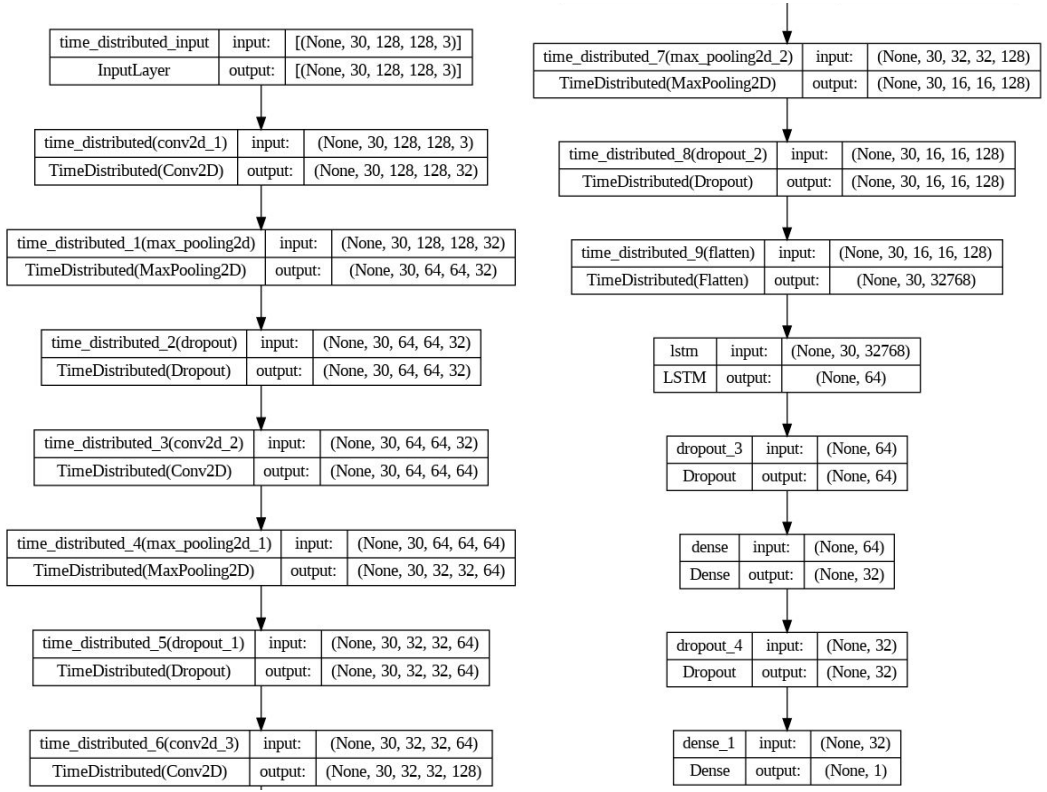

Fig. 2. Model Summary

CNN-LSTM Model

- Processes input video frames using multiple parallel streams
- Conv2D layers for feature extraction
- MaxPooling2D layers for downsampling
- Dropout layers for regularization

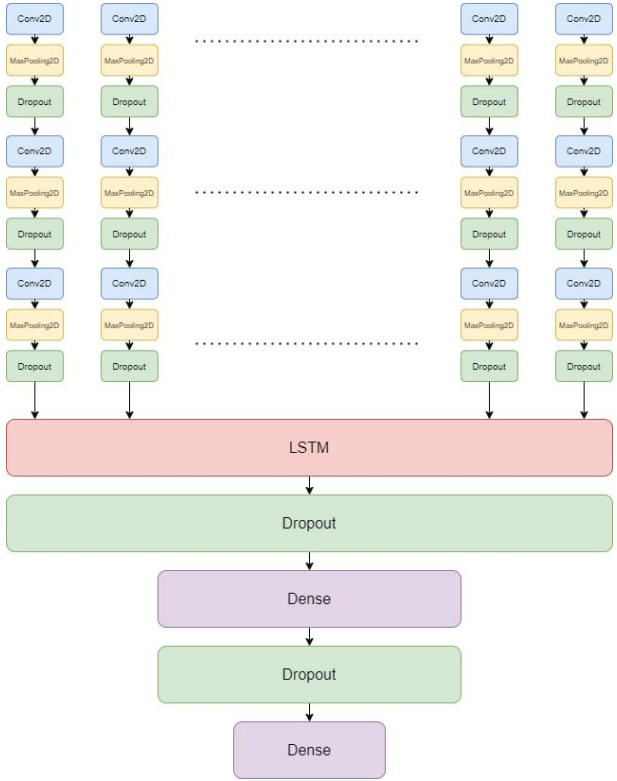

Fig. 3. Model Architecture

Training

- 70-20-10 train-test-validation split
- Trained with 83.5 GB RAM
- Google Colab A100 GPU
- 80-epoch training
- 0.001 learning rate
- Adam optimizer
- 289.9 s training time

Results & Discussion

Model Performance

- Training accuracy of 99.43%
- Validation and test accuracy of 100% each
- Maintains high level of performance with 4 diverse datasets
  - Other vision-based approaches like Lu et al.[8] only used 1-2 datasets
- High accuracy, precision, recall, and AUC
  - Better results than studies like Su et al. [9], who achieved an accuracy of 98.06% on UR Fall Dataset and 94.84% on Multiple Cameras Fall Dataset
- Lightweight architecture

[15] Lu N, Wu D, Wang C, et al. Deep learning for fall detection: three-dimensional CNN combined with LSTM on video kinematic data. IEEE J Biomed Health Inform. 2019;23(1):314-323. Published February 2020.

[16] Su C, Wei J, Lin D, Kong L, Yong Liang Guan. A novel model for fall detection and action recognition combined lightweight 3D-CNN and convolutional LSTM networks. Pattern analysis and applications. 2024;27(1). Published February 2024.

Model Performance

- 5 performance metrics: accuracy, AUC, loss, recall, and precision

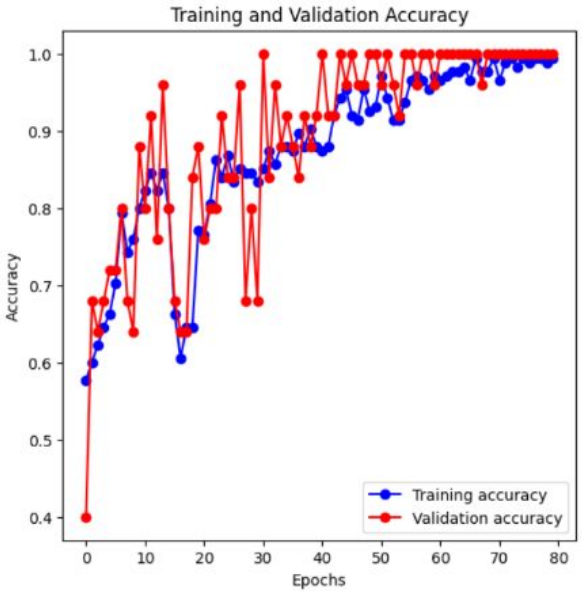

Fig. 4. Training and Validation Accuracy Plot

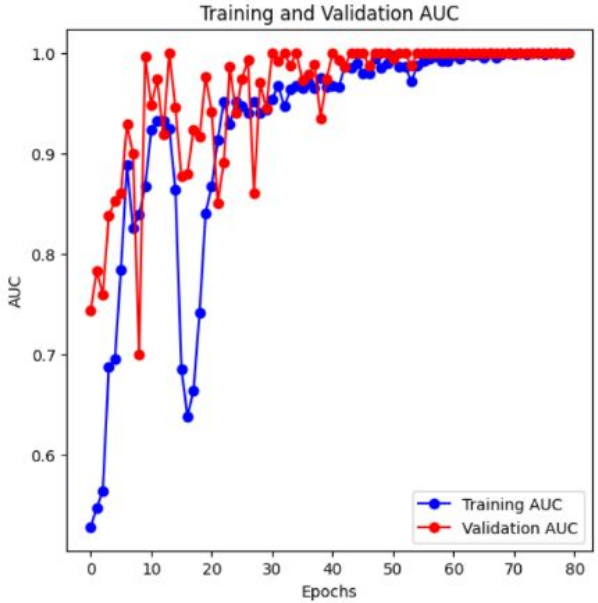

Fig. 5. Training and Validation AUC Plot

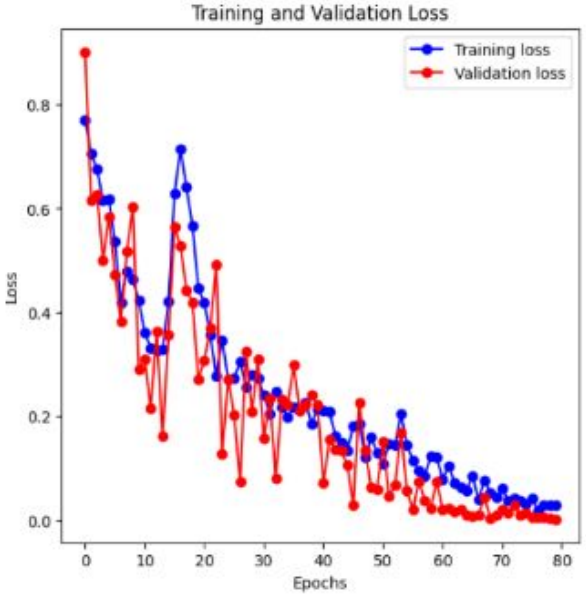

Fig. 6. Training and Validation Loss Plot

Model Performance

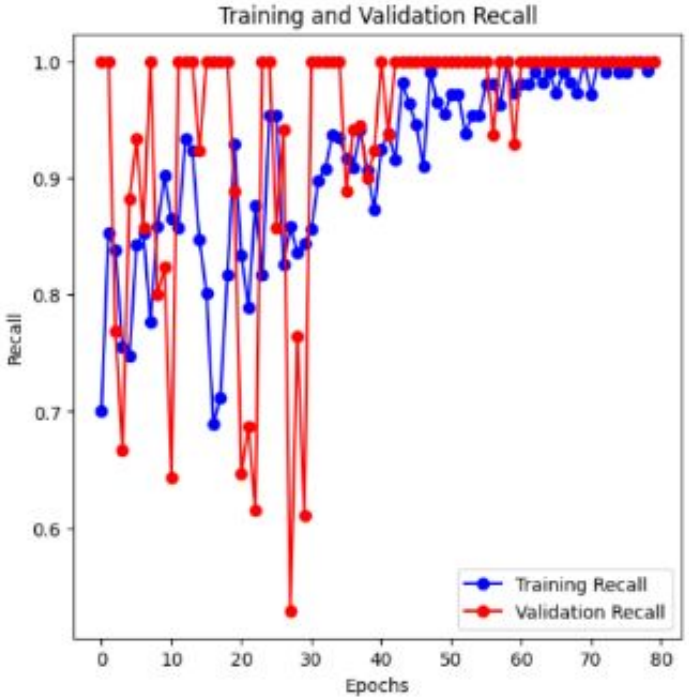

Fig. 7. Training and Validation Recall Plot

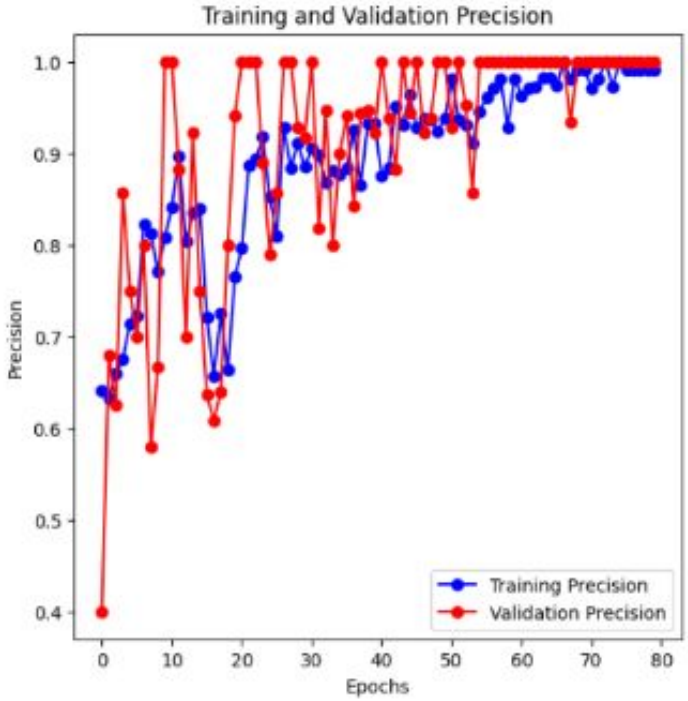

Fig. 8. Training and Validation Precision Plot

Conclusion

Conclusion

- Trained with four diverse datasets
- Validation & testing accuracies near 100%
- 0% false positive rate
- Reliable & practical model

Future Work

Future Work

- Train with more participants
- Simulate falls in different locations/angles
- Multimodal approach- integrate with acoustic detection/wearable devices
- Object detection and body landmark tracking for additional information
- Expand LapseNet to workplace accidents
- Integrate LapseNet into a system that can be connected to security cameras in buildings

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[2] Vaishya R, Vaish A. Falls in older adults are serious. Indian J Orthop. 2020;54(1):69-74. Published 2020.
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https://github.com/sjain2025/LapseNet_Fall_Detection