Implications of Regularization on Human Activity Learning Approaches

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Motivation & Objective

Motivation

- Deep learning based Human Activity Recognition relies heavily on large datasets for generalization
- Learning approaches such as Contrastive Learning, Multi-Instance learning use Data Augmentation Techniques
- Unfair class dependent bias caused by regularization effect explodes while adopting Transfer learning to perform arbitrary downstream tasks

Objective

Analyze the implications of augmentation across the different learning approaches of HAR, aware of all these issues

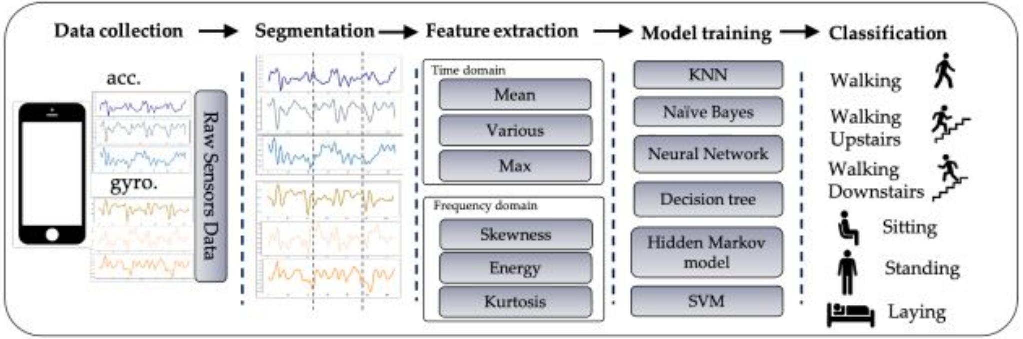
Deliverables

Human Activity recognition models implemented on Tensorflow with class wise accuracies compared across regularization techniques

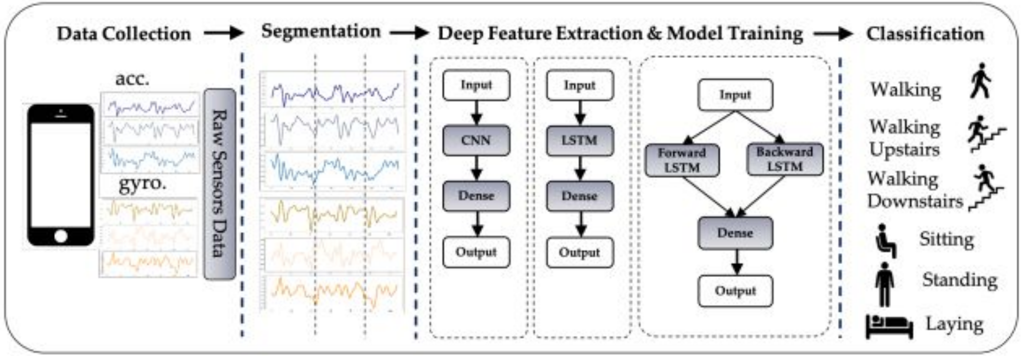
Technical Approach

1. Train State of the Art Model on HAR data and Analyze Baseline Performance
2. Infer the Post Augmentation Model Performance Accuracy and Dependence of Accuracy across Classes
3. Understand the impact of Regularization in boosting performance vs Maintaining fairness in downstream task
4. Benchmark the minimum dataset size needed to achieve target performance utilizing Data Augmentation and minimal % of labelled data.

Technical Approach- Contemporary Approaches



(a) Sensor-based HAR using Machine Learning Approaches



(b) Sensor-based HAR using Deep Learning Approaches

Image from [3]

Technical Approach- DeepConvLSTM

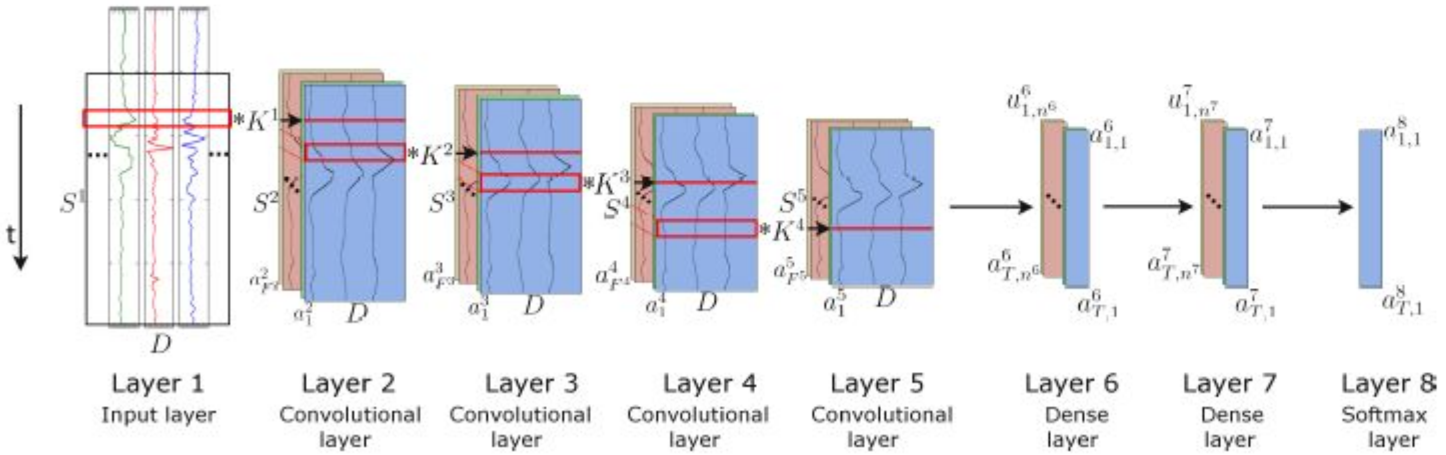


Image from [1]

Results - Data Augmentation

Activity	Baseline	Augmentation 1	Augmentation 2
Walking	0.92	0.93	0.89
Stairs Up	0.92	0.96	0.91
Stairs Down	0.96	0.99	0.99
Sitting	0.89	0.88	0.86
Standing	0.94	0.94	0.92
Lying	0.86	0.84	0.91
Overall Accuracy	92.5	93.4	92.8

Results - Weight Decay

- Here we add a penalty to our loss function that penalises the complexity of the model.
- Penalizing these weights helps the model generalize better to new data and prevents underfitting.
- We use both the L1 and L2 form of regularization for all weight parameters.

Weight Decay Results

Activity	Baseline	Weight Decay
Walking	0.92	0.97
Stairs Up	0.94	0.99
Stairs Down	0.96	0.98
Sitting	0.89	0.92
Standing	0.94	0.91
Lying	0.86	0.90
Overall Accuracy	92.5	94

Next Steps

Compare class accuracies of baseline model with

1) Data augmentation techniques
   - Resampling, Noise addition
   - Resampling for Contrastive Learning[1]
   - Augmentation techniques using generative models. [5]
2) Exploring impact on Large Datasets
   - Datasets like **PAMAP2** are much larger with more instances, hence we could see more pronounced results.[7]
3) Varying model architectures and understanding impact.
   - Experiments with other architectures including vanilla LSTM and comparing results.

Appendix

Dataset Visualization:

Description of UCI-HAR dataset

Activity	Abbreviates	Description	No. of Samples
Walking	Wa	Participant walks horizontal forward in a direct position	1722
Walking (Upstairs)	Wu	Participant walks upstairs	1544
Walking (Downstairs)	Wd	Participant walks downstairs	1406
Sitting	Si	Participant sits on a chair	1777
Standing	St	Participant stands inactive	1906
Laying	La	Participant sleeps or lies down	1944

References

[1] Wang, Jinqiang and Zhu, Tao and Gan, Jingyuan and Chen, Liming and Ning, Huansheng and Wan, Yaping. (2021). Sensor Data Augmentation with Resampling for Contrastive Learning in Human Activity Recognition

[2] Ordóñez, F.J.; Roggen, D. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. *Sensors* **2016**, *16*, 115. https://doi.org/10.3390/s16010115

[3] S. Mekruksavanich and A. Jitpattanakul, “LSTM Networks using Smartphone data for Sensor-based Human Activity Recognition in smart homes,” Sensors, vol. 21, no. 5, p. 1636, 2021

[4] https://archive.ics.uci.edu/ml/datasets/human+activity+recognition+using+smartphones

[5] A. Hoelzemann, N. Sorathiya and K. Van Laerhoven, "Data Augmentation Strategies for Human Activity Data Using Generative Adversarial Neural Networks," *2021 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)*, 2021, pp. 8-13, doi: 10.1109/PerComWorkshops51409.2021.9431046.

[6] Fu, B., Kirchbuchner, F., & Kuijper, A. (2020). Data augmentation for time series: traditional vs generative models on capacitive proximity time series. *Proceedings of the 13th ACM International Conference on PErvasive Technologies Related to Assistive Environments*.

[7] https://archive.ics.uci.edu/ml/datasets/PAMAP2+Physical+Activity+Monitoring