Deep Learning Models for Human Activity Recognition Using Wearable Body Sensors

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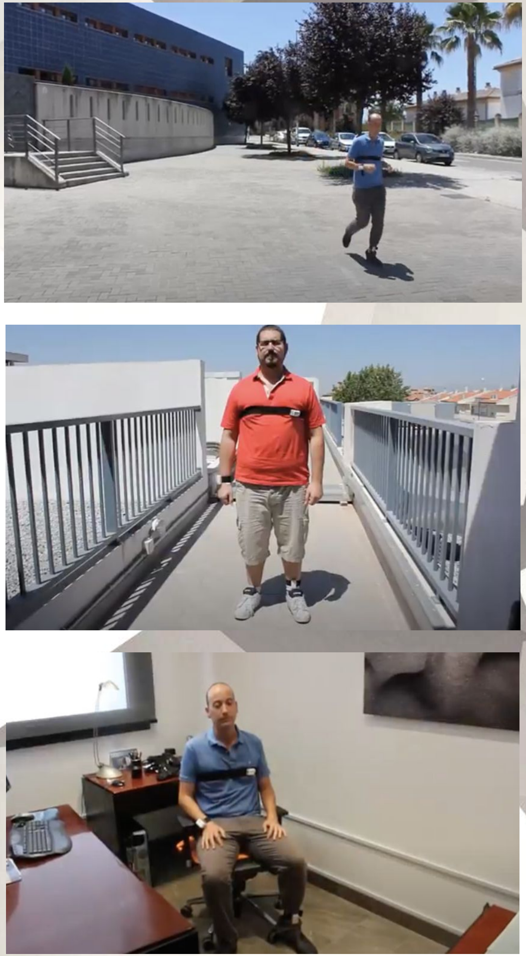
The objective of the project is to develop deep learning models capable of classifying labeled motion data with high accuracy and high generalizability to the Parkinson's population.



[1]

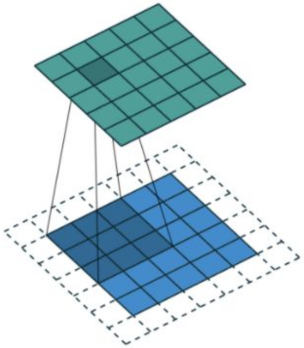
Human activity recognition (HAR) is the challenge of utilizing machine learning algorithms to predict an individual's activity.

This project focuses on HAR through wearable body sensors.

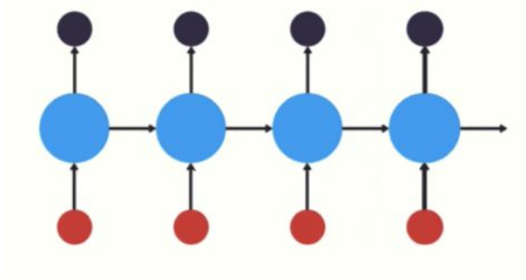
Deep learning has become popular in HAR research as it avoids challenges faced by traditional machine learning methods.

Traditional Methods	Deep Learning Methods
Manual feature engineering	Automatic feature extraction
Requires expert domain knowledge	Domain knowledge independent
Potentially less generalizable	More versatile

CNNs and LSTMs cater to the spatial and temporal properties inherent in motion-based time series data.

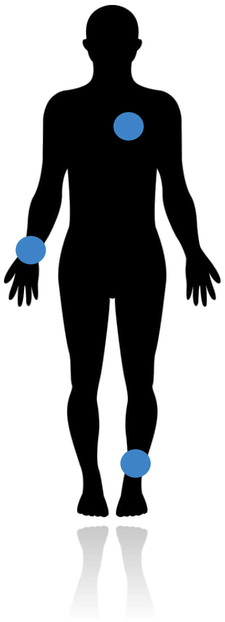


CNNs - spatially deep



LSTMs - temporally deep

Two publicly available activity recognition datasets were used to develop the models.



MHEALTH

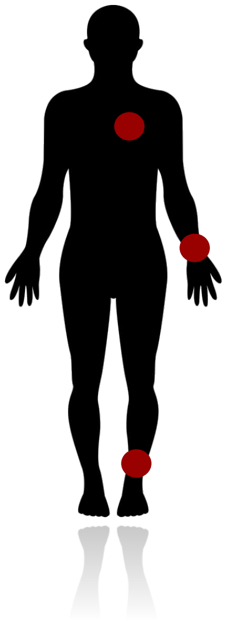
12 activities
10 subjects
❑ Chest ❑ Right Wrist ❑ Left Ankle

[2, 3, 4]

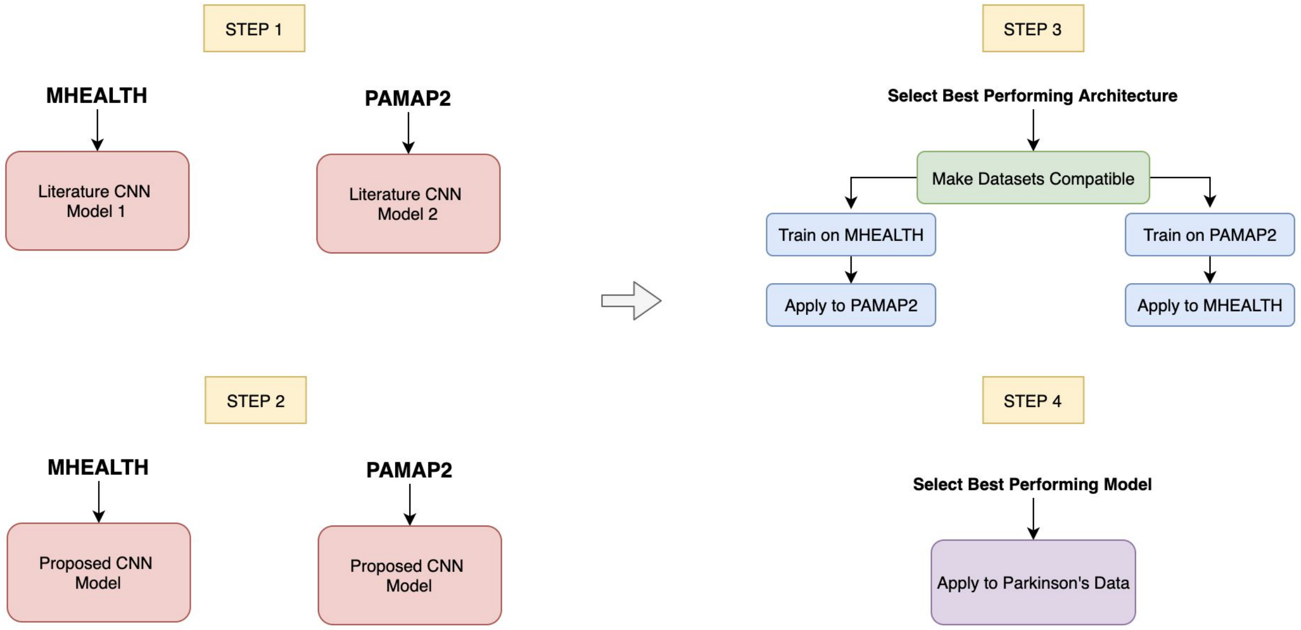
PAMAP2

18 activities
9 subjects
❑ Chest ❑ Dominant Side Wrist ❑ Dominant Side Ankle

[5, 6, 7]



Project implementation is divided into 4 major steps, which include replicating literature models as a benchmark, proposing a unique architecture, testing the best model's generalizability, and applying it to Parkinson's population.



**Repeat for CNN-LSTM*

The goal of the proposed model is to minimize the complexity and maximize generalizability to new data.

- Minimize **complexity** (parameters)
  - Replace flatten/FC layers with global average pooling and batch normalization as suggested by [15]

- Maximize **generalizability**
  - Dropout
  - L1 regularization on convolutional layer with most filters
  - Max pooling

The **PAMAP2 CNN** testing results overall showed comparable performance with less parameters needed.

	Accuracy [min, max from 5 runs]	Weighted F1-Score	Parameters
Rueda et al. [9]	89.11	87.19	3,331,084
Hammerla et al [14]	90.50	89.25	29,724
Proposed Model	**91.62** [89.94, 93.85]	**89.86**	**6,684**

Considerations:

- Literature references had some different data preprocessing methods. One approach was chosen as a standard protocol in order to be consistent with comparison across multiple papers and proposed architecture. Results were still consistent with those reported by the authors.

The **MHEALTH CNN** testing results overall showed comparable performance with less parameters needed.

	Accuracy [min, max from 5 runs]	Weighted F1-Score	Parameters
Chen & Xue [10]	89.29	86.25	56,394
Proposed Model	**92.19** [86.16, 98.44]*	**90.92**	**5,292**

*Consideration: proposed model shows high variance in testing accuracy for MHEALTH

	Accuracy (confidence interval)
Chen & Xue [10]	88.67 (85.38, 91.96)
Jiang & Yin [13]	51.46 (35.35, 67.57)
Ha et al. [11]	88.34 (84.91, 91.78)
Ha & Choi [12]	84.23 (80.01, 88.44)

[8]

The proposed architectures for CNN and LSTM models were able to accurately classify the majority of the data from the other dataset when the fully trained model was cross-tested.

	MHEALTH -> PAMAP2 (Accuracy)	**PAMAP2 -> MHEALTH** (Accuracy)	Parameters
CNN (Proposed)	76.04	73.62	4,764
CNN-LSTM (Proposed)	76.01	75.22	13,296

Future consideration:

- Accelerometers and gyroscopes were calibrated to have different scales per dataset and these were not yet made compatible. Scaling the data so their ranges match can help improve performance. These current results can serve as a baseline.

In summary, the proposed CNN architecture showed comparable performance to various literature results with less parameters needed. When proposed CNN and CNN-LSTM models were cross applied on both datasets, they showed good generalizability with more room for improvement.

Final Remarks

Future Work (to be continued through DIS):

- Evaluate **CNN-LSTM** hybrid models from literature for comparison to proposed CNN-LSTM
- Further **evaluate papers** to explore more model results and ideas
- Apply to **Parkinson's patients data**

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Thank you!