DEEP LEARNING FOR BIOMEDICAL HEALTH DATA:

A Simple Framework for Contrastive Learning (SimCLR) for Human Activity Recognition (HAR) in individuals with Parkinson’s Disease (PD)

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OBJECTIVE

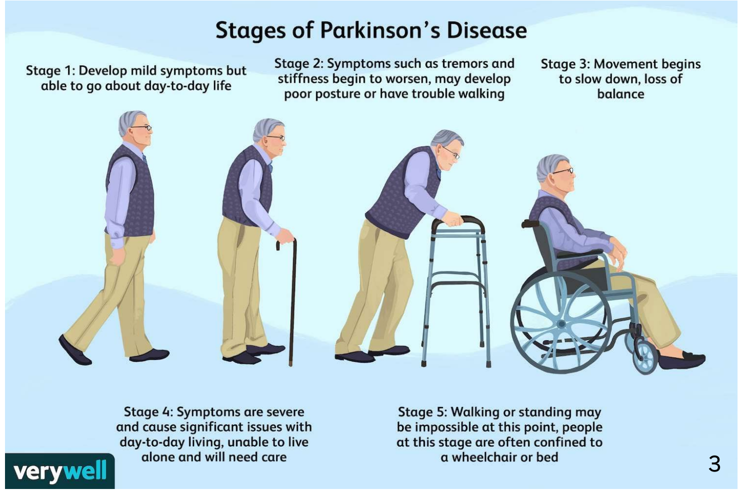
Currently, this project aims at creating an AI model based on the most recent advances of machine learning techniques that can acquire and analyze data from individuals with Parkinson's Disease and accurately identify when the individuals perform daily living activities.

INTRODUCTION

Parkinson's Disease is a chronic movement disorder that causes tremors and slowing of movement[1]. Over 1 million people[2] have been affected by this disease in the United States alone, and taking steps to improve patients' quality of life has a multitude of implications for the future.

By using the latest models in Machine Learning, we will be able to study everyday actions of those with Parkinsons disease and methodically measure the different relationships that exist between tremors.

1. *Parkinson's disease - Symptoms and causes - Mayo Clinic*. (2023, May 26). Mayo Clinic. https://www.mayoclinic.org/diseases-conditions/parkinsons-disease/symptoms-causes/syc-20376055
2. *Statistics*. (n.d.). Parkinson's Foundation. https://www.parkinson.org/understanding-parkinsons/statistics
3. Bottaro, A. (2021). 10+ Facts About Parkinson's Disease. Verywell Health. https://www.verywellhealth.com/facts-about-parkinsons-disease-5200700
4. Beck, J., PhD. (2022). Parkinson Disease Prevalence Severely Underestimated: Parkinson's Foundation Prevalence Project. Neurology Advisor. https://www.neurologyadvisor.com/topics/movement-disorders/parkinson-disease-prevalence-severely-underestimated-parkinsons-foundation-prevalence-project/
5. Sandra. (2021). Machine learning in industry. ATRIA Innovation. https://www.atriainnovation.com/en/machine-learning-in-industry/



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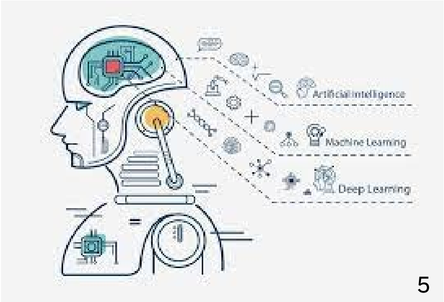

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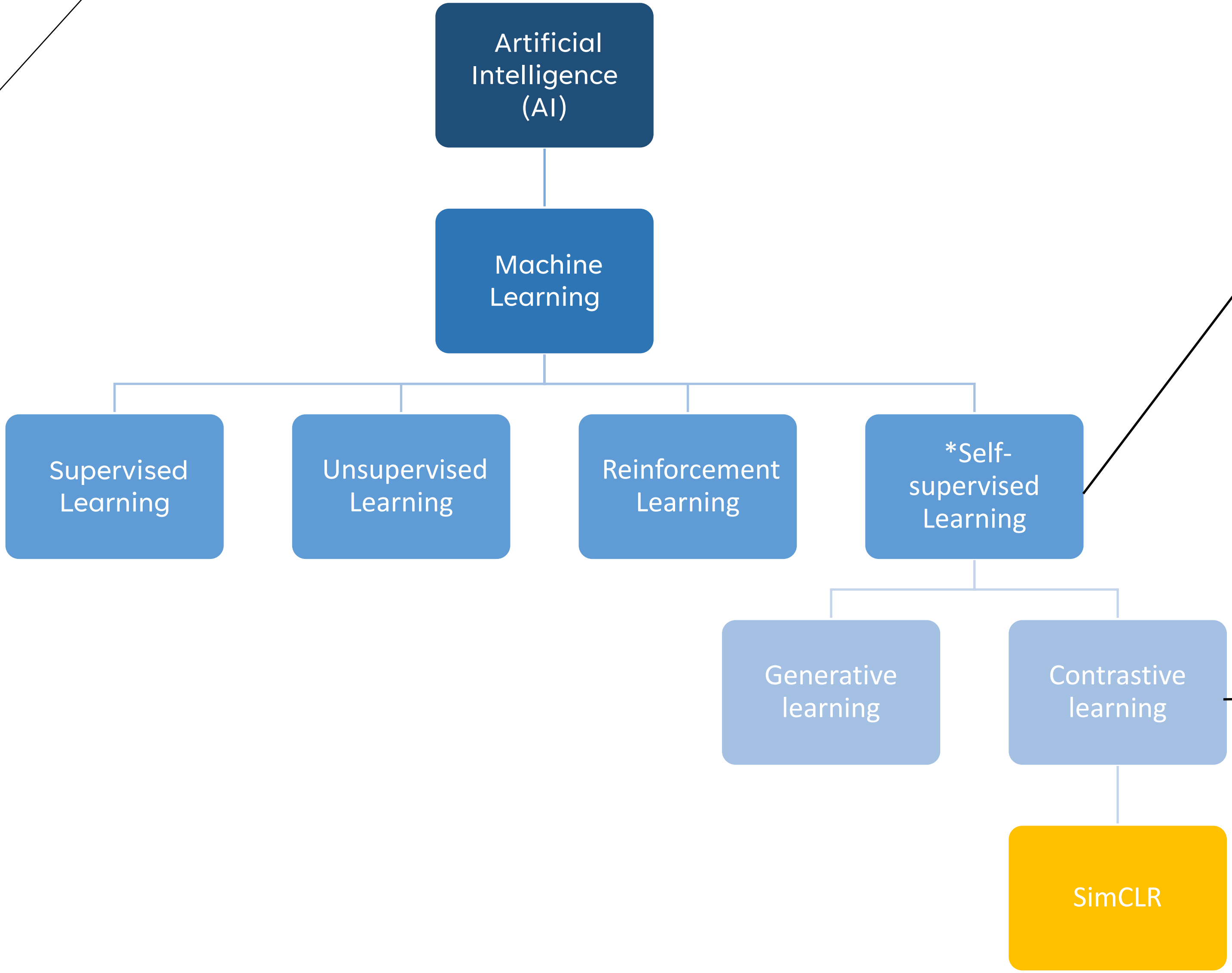
TYPES OF MACHINE LEARNING



learn representations from unlabeled data that can be used in later tasks

maximize agreement (similarity) between 'positive pairs' (i.e., data of the same type) and minimize agreement (i.e., maximize difference) between 'negative pairs' to learn to extract valuable features from the data

REFERENCE RESEARCH

Chen, Ting, et al. "A simple framework for contrastive learning of visual representations." *International conference on machine learning*. PMLR, 2020.

- Concept introduced by Google
- Utilized for images

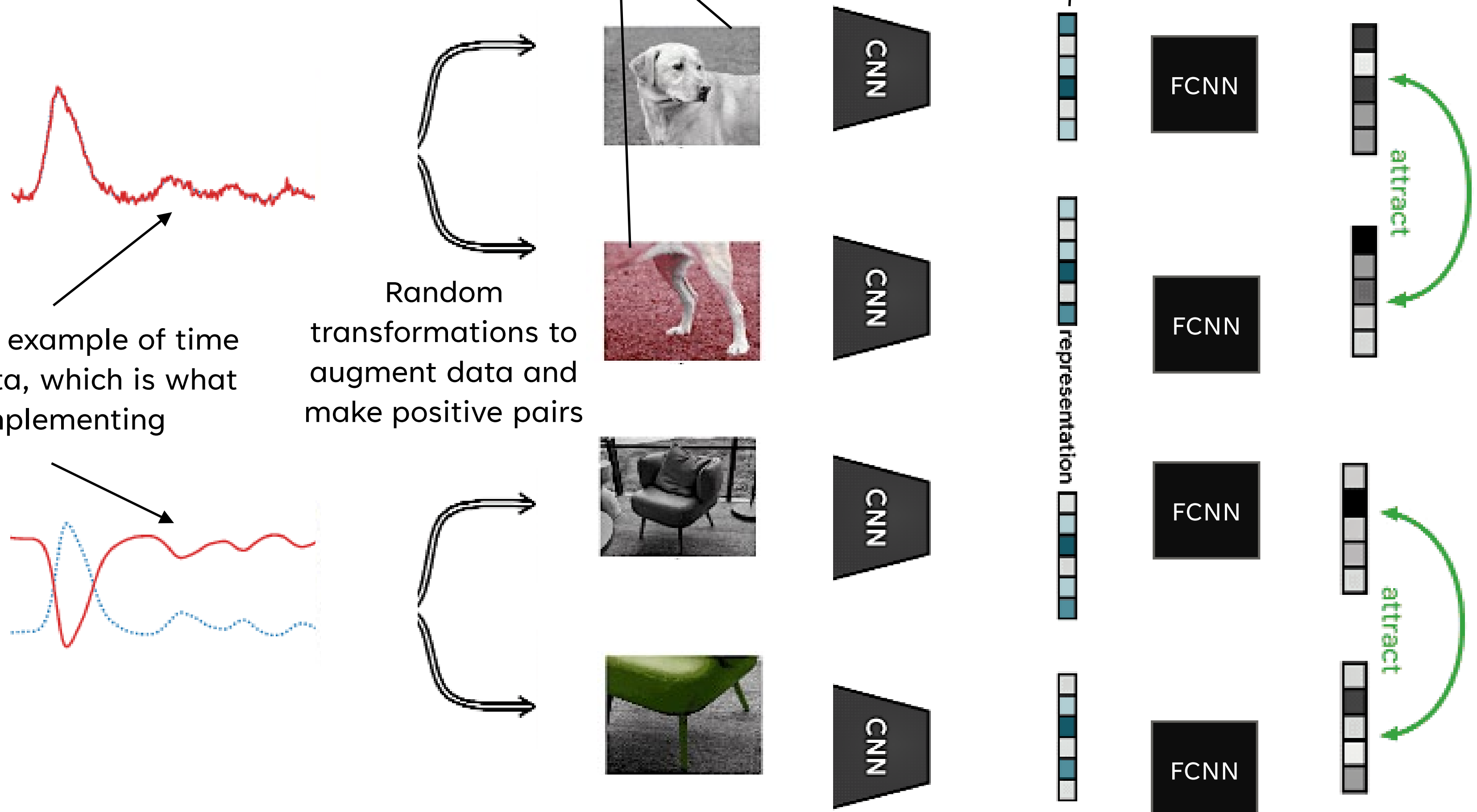
Tang, Chi Ian, et al. "Exploring contrastive learning in human activity recognition for healthcare." *arXiv preprint arXiv:2011.11542* (2020).

- Used for HAR (Human Activity Recognition)
- Time Series Data

SIMCLR

Positive pairs, different view of the same piece of data

Characteristics of the augmented data, notable features + aid in other tasks



This is an example of time series data, which is what we are implementing

Random transformations to augment data and make positive pairs

Enumerates how similar (the agreement) between the augmented data is

Takes data into format in which representations can be extracted

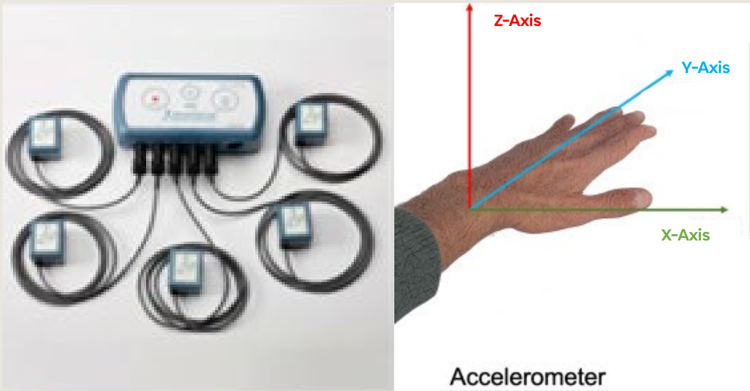
Fully Connected Neural Network: Takes representations and transforms it so a loss (error) function can be applied

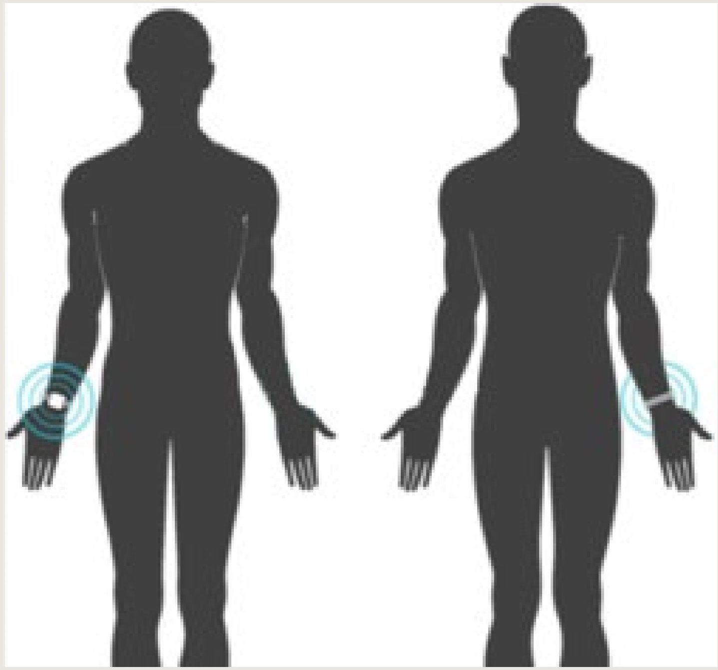
Adapted from *SimCLR Visually Explained*. (2022, March 5). Vasudev Sharma. https://vasudev-sharma.github.io/posts/2022/03/SimCLR-visually-explained/

DATASET AND SETUP

Data Collection

- 15 subjects performing 7 activities
  - Performed in a lab setting
  - Activities: ambulation, arms resting, cutting, dressing, drinking, groceries, hair brushing
- Subjects had varying degrees of progression of Parkinsons'
- Tri-axial accelerometer sensors on the most affected wrist





1 **Analyze** and break down the SimCLR model components to understand function and impact on results

2 **Run** the model on public dataset to achieve comparable results to *Exploring Contrastive Learning in Human Activity Research for Healthcare*

3 **Prepare** and **preprocess** PD dataset to a utilizable format and finetuned the model as needed. Choose following transformations: noise, scaling, rotation, negation, time flip, permutation, time warp, and channel shuffle.

4 **Train** the model and **evaluate** its performance by computing the F1 weighted score for every data transformation. The model is trained on 14 subjects and tested on one subject

5 **Compare** to a fully supervised model under the same conditions as SimCLR as current state-of-the-art comparison

METHODOLOGY

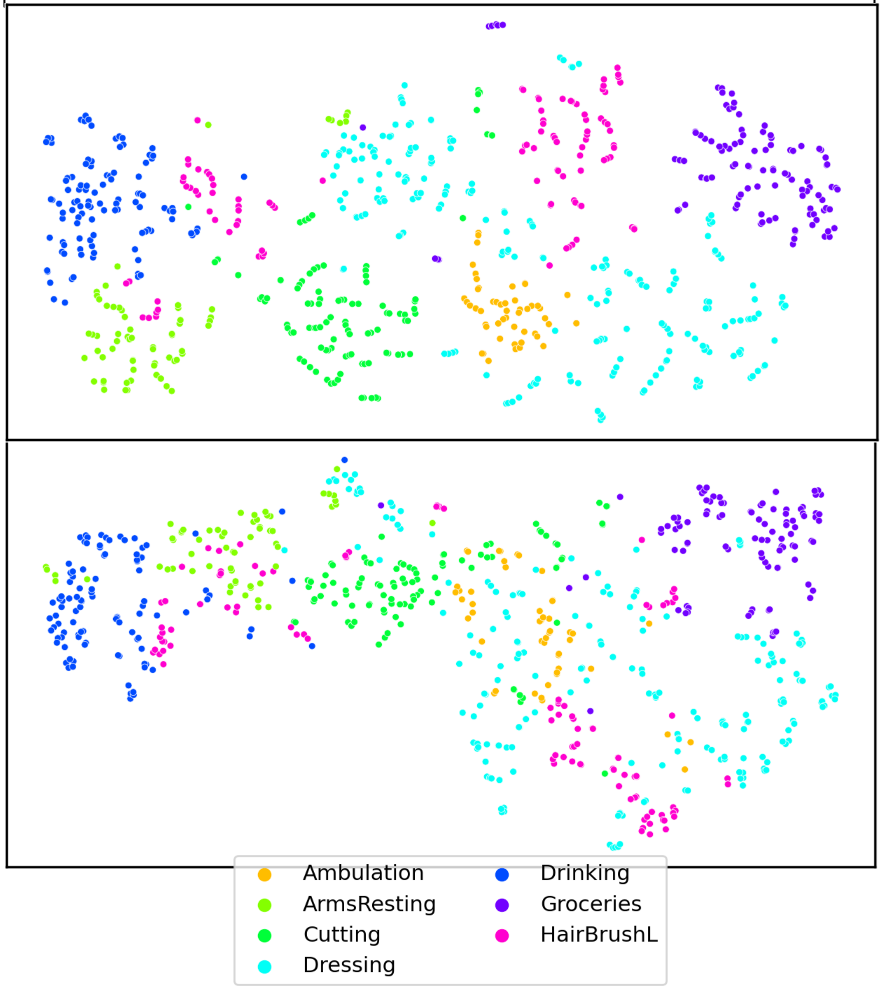
RESULTS: AVERAGE F1 WEIGHTED VALUES FOR EACH TRANSFORMATION

Full HAR Model: Least Validation Loss								
noise	71.42	71.80	71.54	68.98	71.37	76.08	**78.97**	62.17
scale	70.29	69.14	71.67	68.96	65.78	75.85	**77.93**	64.74
rotation	71.57	71.98	59.03	72.81	64.28	75.88	61.55	63.55
negate	70.84	66.51	66.02	61.49	67.58	75.20	**78.41**	61.21
time flip	71.86	69.92	65.73	68.96	68.33	75.44	63.96	57.27
permuted	**77.93**	74.94	76.28	75.56	73.35	75.29	74.01	59.51
time warp	**77.40**	71.75	71.35	66.25	**78.69**	**79.28**	72.50	74.83
channel shuffle	64.89	63.08	69.73	55.06	49.43	61.46	71.03	58.48
	noise	scale	rotation	negate	time flip	permuted	time warp	channel shuffled

Fully Supervised: 76.61

Top 5 Full HAR Transformations:			
Accuracy:	Transformation 1	x	Transformation 2
79.28	Time Warped	x	Permutated
78.97	Noised	x	Time Warped
78.69	Time Warp	x	Time Flip
78.41	Negate	x	Time Warp
77.93	Permutated	x	Noised

Feature Graph: Supervised (top) vs Self-supervised (bottom)



RESULTS: AVERAGE F1 WEIGHTED VALUES FOR EACH SUBJECT AS TEST (USING THE BEST TRANSFORMATIONS)

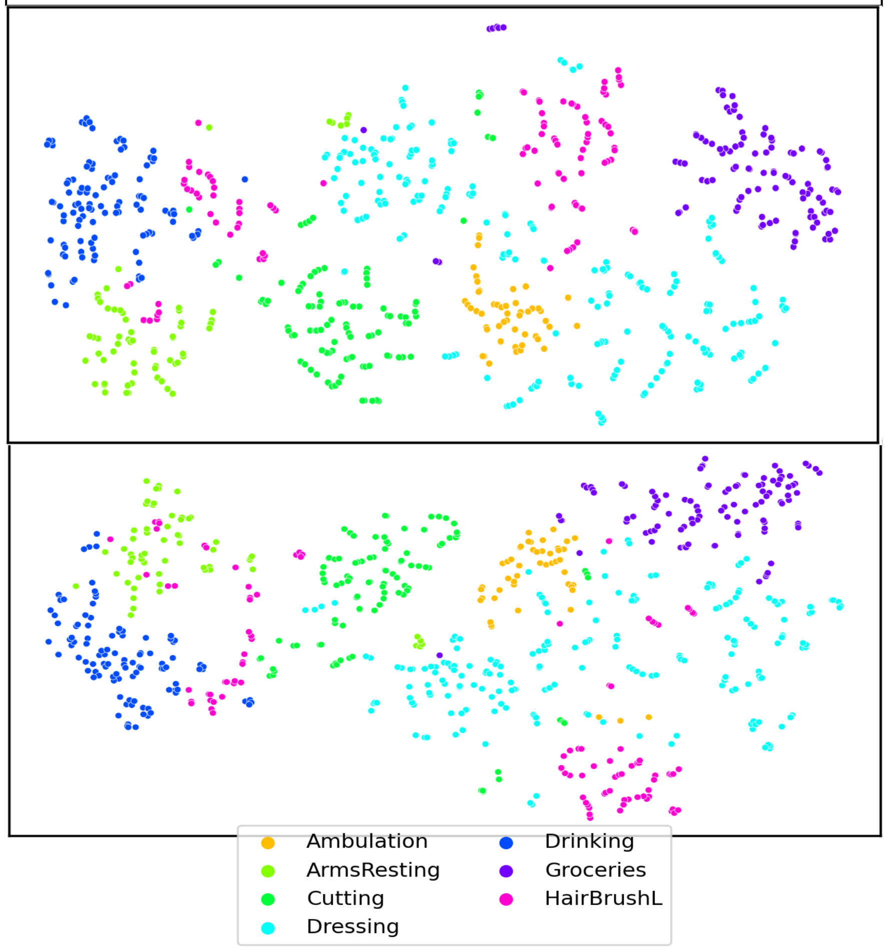
Subject Wise F1 Weighted Score					
noised	61.44	63.00	61.03	64.44	**66.40**
scaled	63.30	62.22	60.86	59.93	62.74
negated	61.92	62.21	60.92	62.31	64.06
permutated	63.49	63.53	63.81	65.04	**67.92**
time_warp	**67.15**	65.95	65.27	63.55	**68.00**
	noised	scaled	negated	permutated	time_warp

Fully Supervised: 66.14

Top 4 Transformations:

Accuracy:	Transformation 1	x	Transformation 2
68.00	Time Warped	x	Time Warped
67.92	Permutated	x	Time Warped
67.15	Time Warped	x	Noised
66.40	Noised	x	Time Warped

Feature Graph: Supervised (top) vs Self-supervised (bottom)



CONCLUSION AND FUTURE WORK

SimCLR showed better results working with Parkinson data than state-of-the-art models, like a fully-supervised model. It provided better accuracy in identifying activities performed by people with Parkinson's disease.

These results can lead to further research in utilizing SimCLR to identify the severity of tremors in patients and be utilized as a tool to distinguish how affected a patient is.

These models can aid healthcare professionals identify the effectiveness of medication.

THANK YOU

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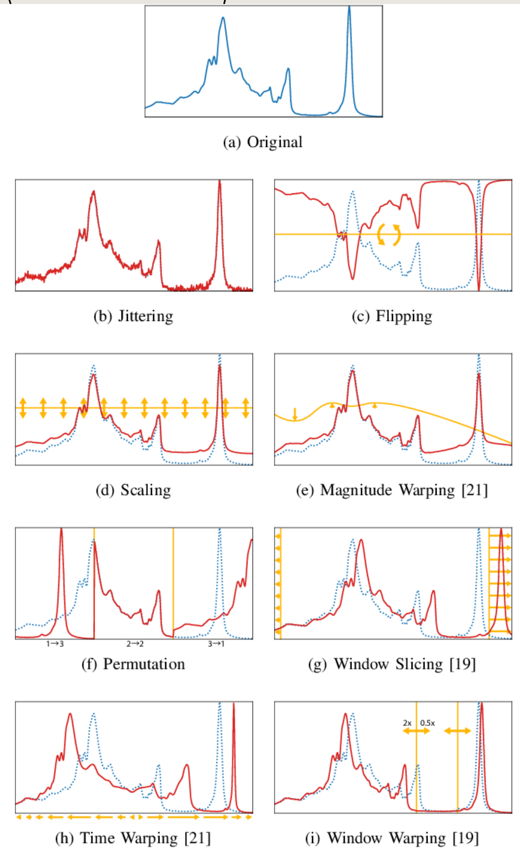
APPENDIX



The ***F1 score*** can be interpreted as a harmonic mean of precision and recall values, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

$$F1 = 2 * (precision * recall) / (precision + recall)$$

The ***F1 Weighted Score*** accounts for imbalances between label values.

Precision: ratio of 'true positive' samples to all samples

Recall: ratio of 'true positive' samples to all positive samples

T-SNE Graph: t-distributed stochastic neighbor embedding

- An unsupervised, non-linear technique primarily used for data exploration and visualizing high-dimensional data[1].
- The t-SNE algorithm calculates a similarity measure between pairs of instances in the high dimensional space and in the low dimensional space. It then tries to optimize these two similarity measures using a cost function[1]

1.Violante, A. (2018, August 30). *An introduction to T-Sne with python example*. Medium. https://towardsdatascience.com/an-introduction-to-t-sne-with-python-example-5a3a293108d