

# A DATA EFFICIENT VISION TRANSFORMER FOR ROBUST HUMAN ACTIVITY RECOGNITION FROM THE SPECTROGRAMS OF WEARABLE SENSOR DATA

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## Abstract

- Introduces the Data Efficient Separable Transformer (DeSepTr) architecture for Human Activity Recognition (HAR).
- Utilizes a lightweight computer vision model to train a Vision Transformer (ViT) on spectrograms from wearable sensor data.
- Achieves strong results on HAR tasks, including surface condition recognition and activity recognition.
- Outperforms ResNet-18 by 5.9% on out-of-distribution (OOD) test data accuracy for surface condition recognition.
- Enables ViTs to learn from limited labeled training data and generalize to data from participants outside of the training cohort.

## Introduction

- Internet of Things (IoT) and mobile-technologies are collecting massive amounts of data for mobile health (mHealth) applications.
- Deep Learning (DL) is a potent tool for analyzing data from accelerometers and gyroscopes.
- Transformers are gaining prominence as a powerful method in both the Natural Language Processing (NLP) and Computer Vision (CV) fields.
- Limited work has explored the application of training Vision Transformers (ViT) for analyzing wearable sensor data.

## Human Activity Recognition

- Human Activity Recognition (HAR) can be accomplished using data from body-worn accelerometers and gyroscopes.
- ML and DL techniques have demonstrated successful applications in HAR, including tasks such as exercise recognition [7] and surface condition recognition [4].
- We evaluate our methods across the following datasets: Uneven and irregular surface condition recognition [2], activity recognition [5, 6], and the detection of Freezing-of-Gait (FoG) events from patients with PD [1].
- The proposed methods are used to solve supervised classification problems following the pipeline in Figure 1.

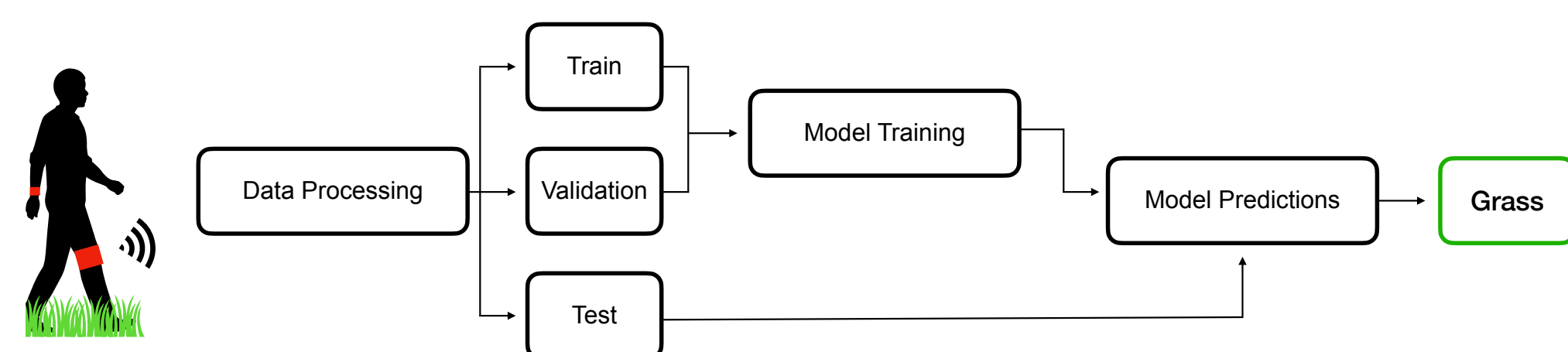


Fig. 1: Supervised ML pipeline for HAR

## DeSepTr

- The strong inductive bias of ViTs may pose a challenge in HAR due to the requirement of a large training dataset, which is often scarce in this domain.
- Our proposed approach, the Data Efficient Separable Transformer (DeSepTr), addresses this challenge by training the Transformer on a 'smashed' data representation using knowledge distillation (KD) techniques.
- The DeSepTr architecture utilizes spectrograms generated from wearable sensor data to train the separable transformer (SepTr) model for HAR.
- The approach shows promising results in improving the model's predictive capabilities on out-of-distribution (OOD) data.

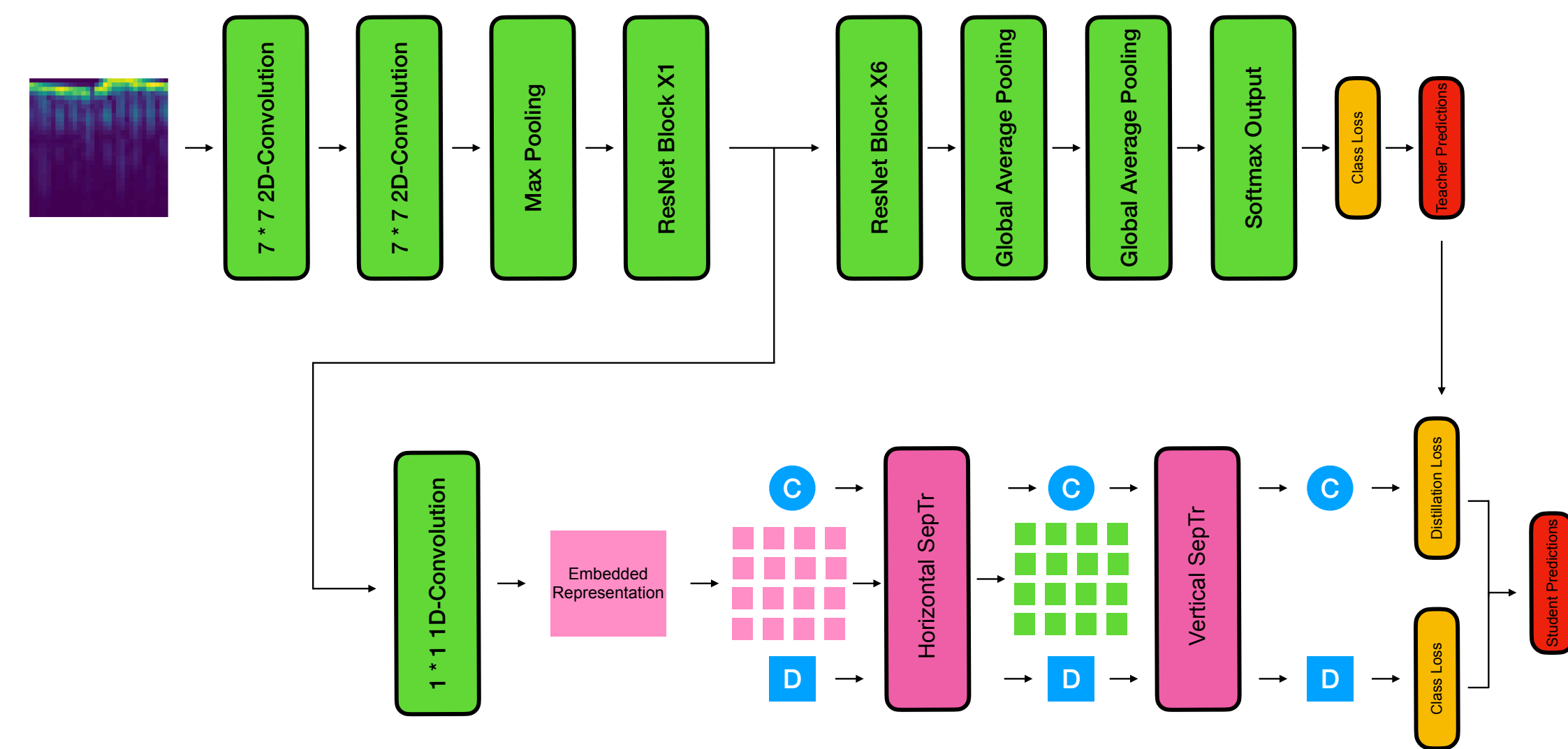


Fig. 2: Architecture of DeSepTr

True Label	DeSepTr: Validation Dataset										DeSepTr: Test Dataset									
	FE	CS	StrU	StrD	SlipU	SlipD	Bnkl	Bnkl	GR		FE	CS	StrU	StrD	SlipU	SlipD	Bnkl	Bnkl	GR	
FE	77	0	0	0	0	0	17	4	2		0	3	0	0	0	0	21	13	0	
CS	2	98	0	0	3	0	7	0	7		0	28	0	0	9	1	4	1	0	
StrU	0	0	92	0	0	0	0	0	0		0	0	36	0	0	0	0	0	0	
StrD	0	0	1	87	0	0	0	0	0		0	0	0	34	0	0	0	0	0	
SlipU	0	0	0	0	161	0	0	0	0		0	6	0	0	60	0	0	0	0	
SlipD	6	1	0	0	4	138	3	9	0		0	0	0	0	0	64	0	1	0	
Bnkl	3	3	0	0	3	3	95	5	4		0	1	0	0	5	0	34	0	3	
Bnkl	6	0	0	0	0	0	7	104	1		0	1	0	0	0	5	3	35	0	
GR	2	6	0	0	2	0	4	3	88		0	3	0	0	15	6	6	6	3	

True Label	SepTr: Validation Dataset										SepTr: Test Dataset									
	FE	CS	StrU	StrD	SlipU	SlipD	Bnkl	Bnkl	GR		FE	CS	StrU	StrD	SlipU	SlipD	Bnkl	Bnkl	GR	
FE	86	4	0	0	0	1	4	4	1		0	24	0	0	3	5	2	3	0	
CS	1	108	1	0	1	0	3	2	1		0	15	0	0	9	17	2	0	0	
StrU	0	0	91	1	0	0	0	0	0		0	0	36	0	0	0	0	0	0	
StrD	0	0	0	88	0	0	0	0	0		0	0	0	34	0	0	0	0	0	
SlipU	1	0	0	0	159	0	1	0	0		3	31	0	0	29	0	3	0	0	
SlipD	1	2	0	0	1	155	0	1	1		0	6	0	0	0	59	0	0	0	
Bnkl	2	2	0	0	3	1	106	2	0		0	19	0	0	4	18	2	0	0	
Bnkl	1	2	0	0	0	1	6	108	0		3	26	0	0	5	4	0	6	0	
GR	2	4	0	0	0	2	0	97			2	7	0	0	11	13	1	3	2	

Fig. 3: Confusion Matrices comparing the performance of the DeSepTr and the SepTr supervised ML algorithms for predicting uneven and irregular surface conditions from wearable sensor data. The test dataset contains data from a client who did not partake in the training of the centralized model.

## Future Work

- Adapt our approach for Federated Learning [3]
- Application of our approach to a clinical dataset for medical applications.
- Implementing the FL approach for the medical application.

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