Self-SLAM: A Self-Supervised Learning Based Annotation Method to Reduce Labeling Overhead

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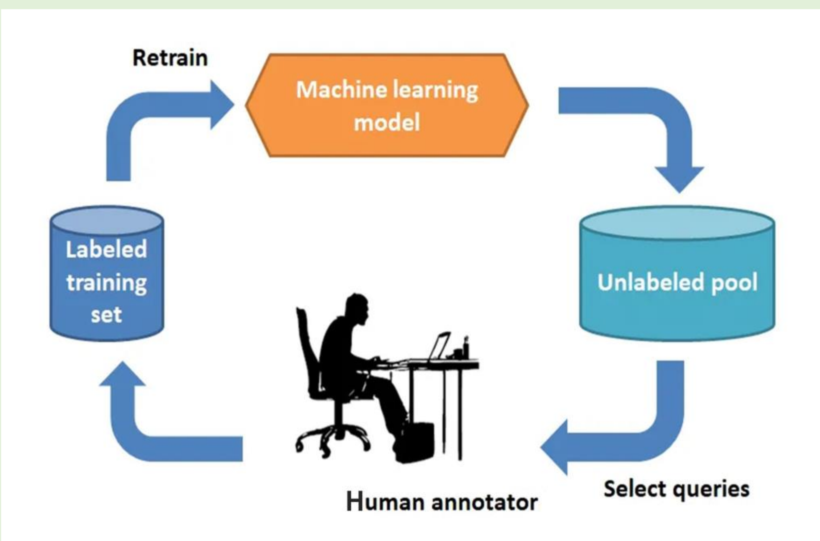
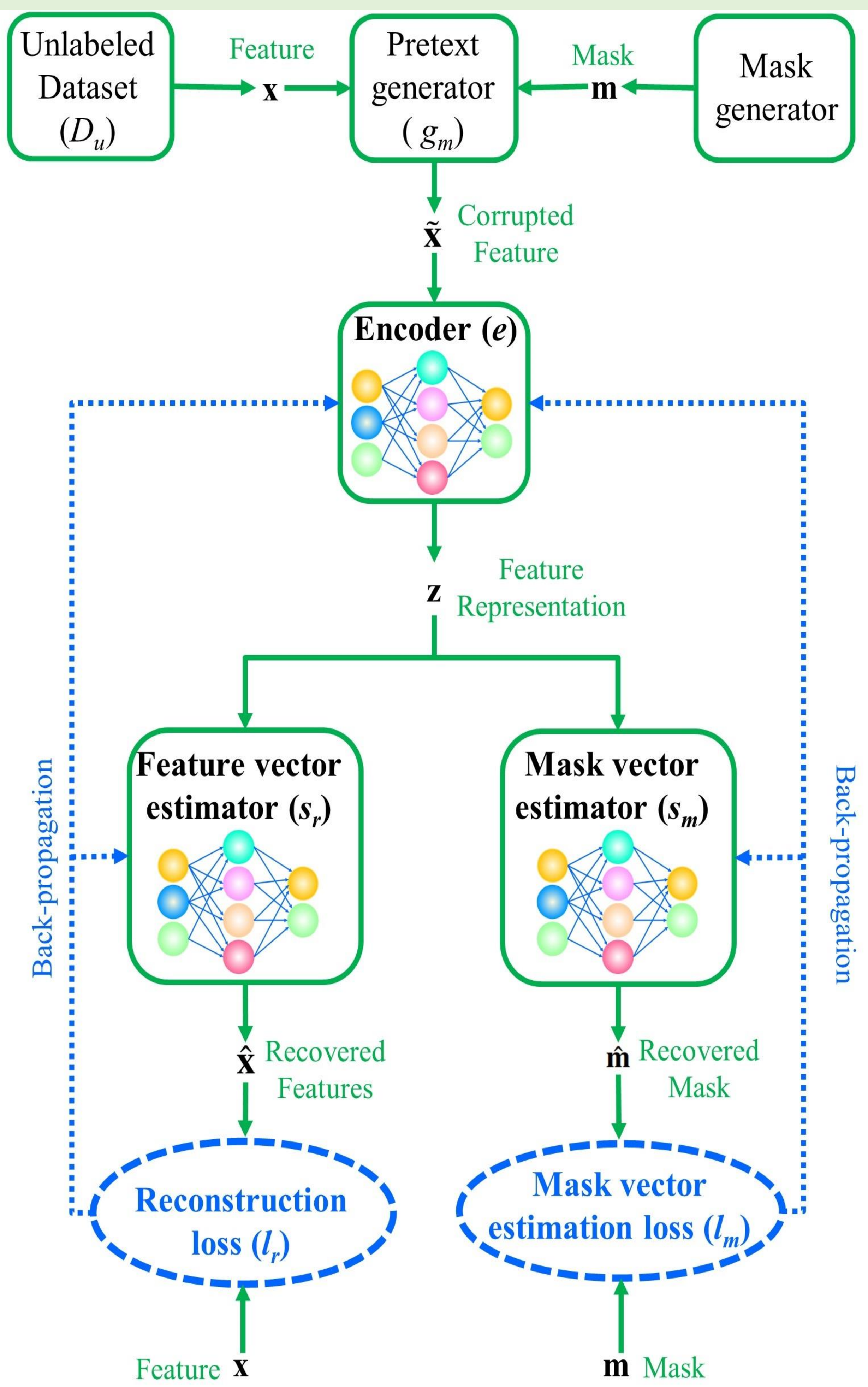
Introduction

•Deep Neural Networks need large labeled datasets for accuracy.
•Manual annotation is costly, time-consuming, and error-prone.
•**SSLAM** (Self-Supervised Learning-based Annotation Method) reduces annotation overhead using self-supervised learning.
•Introduces a novel *log-cosh* loss function to handle noisy labels effectively, ensuring robust learning.

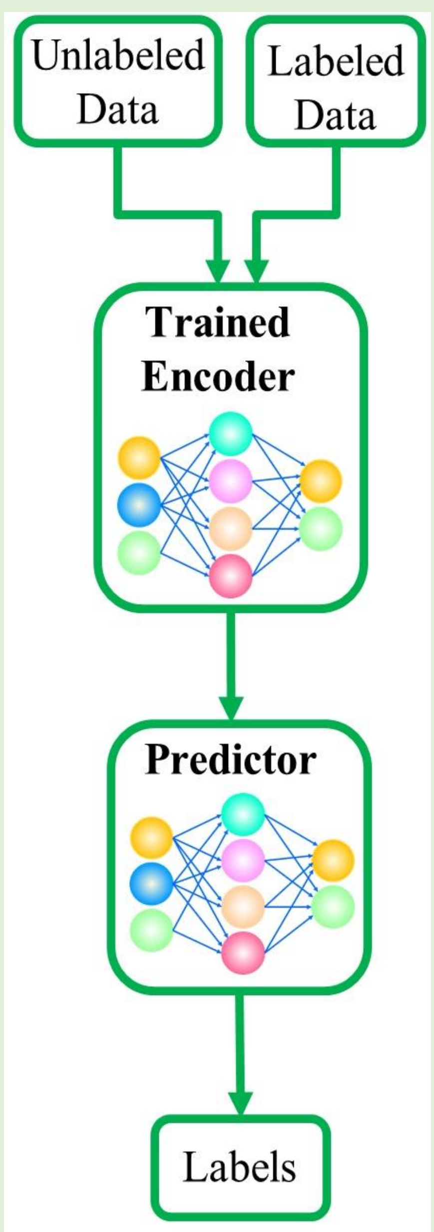


Methodology

- Generates labels from unlabeled data using **Feature Vector Estimation** and **Mask Vector Estimation**.
- Utilizes a parameterized Elliot activation function to enhance the encoder's representation learning.
- **Log-Cosh Loss Function,** defined as `L(x) = log(cosh(x))`, Combines MSE's smoothness with MAE's robustness to outliers for handling noisy labels.
- **Parameterized Elliot Activation Function:** Improves encoder learning and accuracy in label generation.



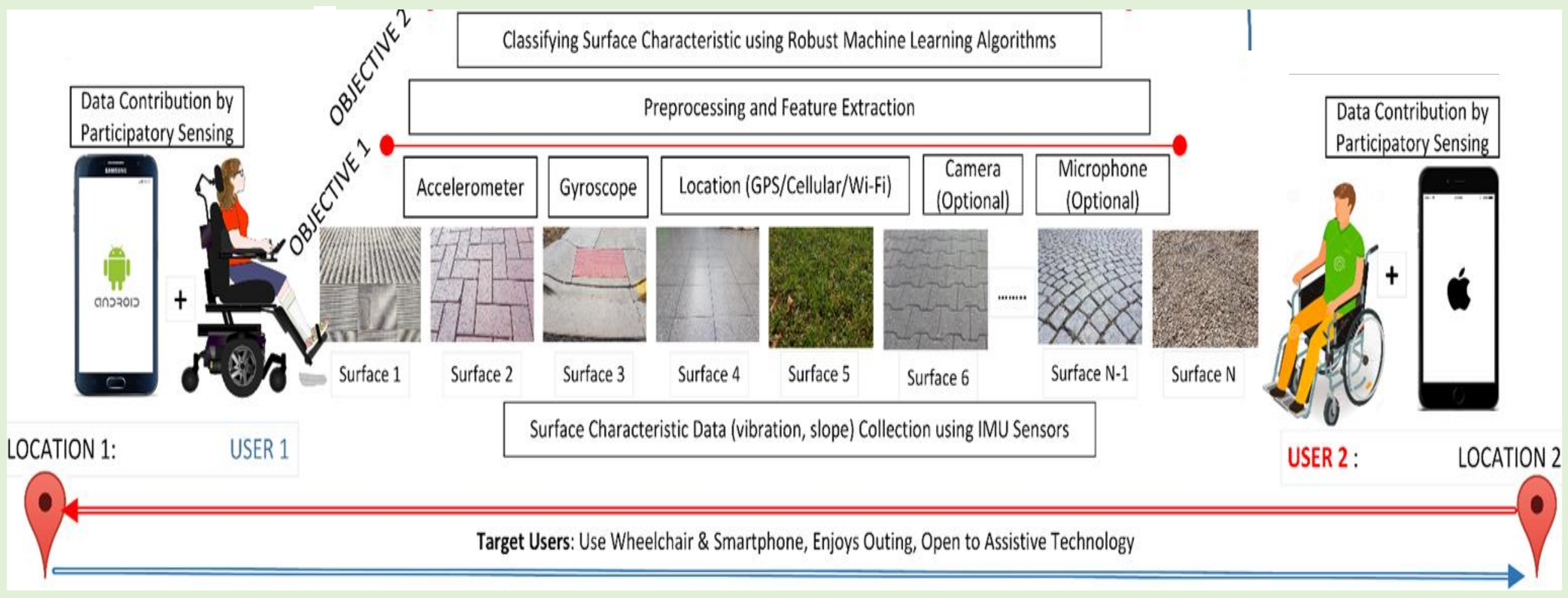
Block diagram of the Self-SLAM framework.



This model generates labels using trained encoder and predictor network.

Datasets

1. **Wheelchair Vibration Dataset:** Surface classification based on wheelchair-induced vibration data.



2. **CASE Dataset:** Continuous emotion annotations using physiological signals.

Results

Surface Classification (Wheelchair Dataset):
SSLAM achieves 71.65% accuracy despite class imbalance in the dataset, surpassing MLP, XGBoost, and the state-of-the-art VIME baseline.

Emotion Annotation (CASE Dataset):
SSLAM records 90.01% accuracy for valence and 89.79% for arousal, outperforming traditional supervised methods and VIME.

Model Type	Wheelchair data (85-15% split)		CASE data (85-15% split)	
	Accuracy	F1 Score	Valence Accuracy	Arousal Accuracy
MLP	0.6740 ± 0.0211	0.6704 ± 0.0054	0.8130 ± 0.0040	0.7993 ± 0.0013
Logistic Regression	0.4463 ± 0.0020	0.4063 ± 0.0012	0.6901 ± 0.0012	0.6806 ± 0.0010
XGBoost	0.6305 ± 0.0089	0.6304 ± 0.0029	0.7330 ± 0.0009	0.7339 ± 0.0022
VIME	0.6366 ± 0.0393	0.6065 ± 0.0381	0.6917 ± 0.0051	0.7213 ± 0.0042
SSLAM	0.7165 ± 0.0054	0.7120 ± 0.0067	0.9001 ± 0.0024	0.8979 ± 0.0045

Takeaways

•SSLAM reduces data labeling costs, enabling wider machine learning applications with large-scale unlabeled datasets.
•By leveraging a novel log-cosh loss function and self-supervised learning, SSLAM improves label quality and model performance.
•Future work will focus on addressing class imbalance and enhancing scalability across varied datasets.

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SSLAM Paper **LinkedIn Profile**

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