Time Series Classification Using Activity Recognition System Based on Multisensor Data Fusion (AReM)

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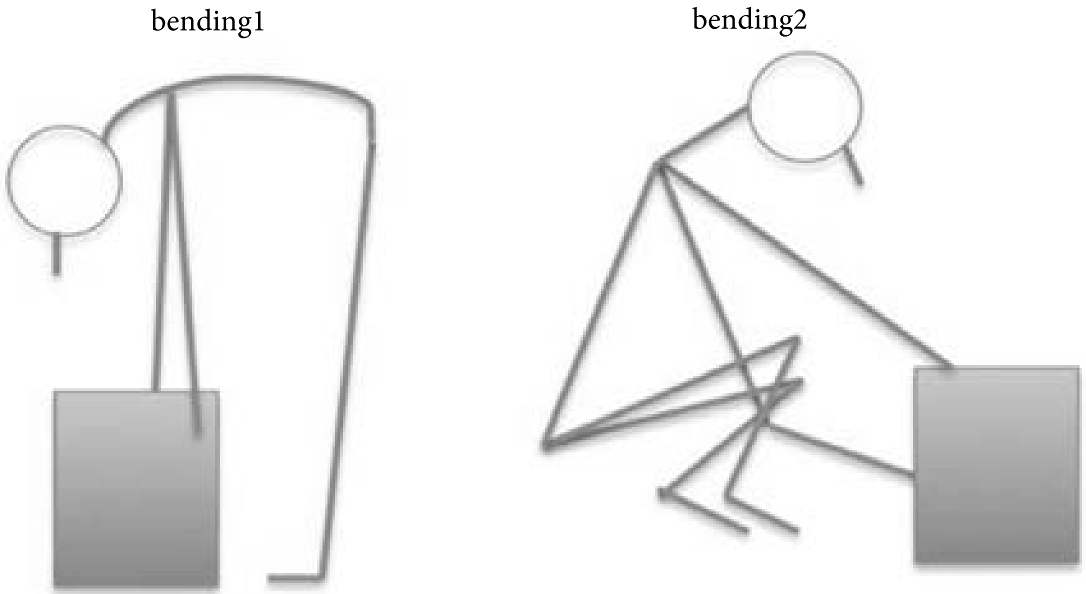
Problem Statement

This project focuses on utilizing the multivariate time series dataset (AReM) and involves preprocessing and augmenting the data before testing it with three different deep learning models: CNN, LSTM, and Transformer-Encoder.

Challenge: A major challenge was managing the large volumes of data produced by wearable technologies. The main issue was not merely collecting the data but also interpreting it effectively to improve user experiences.

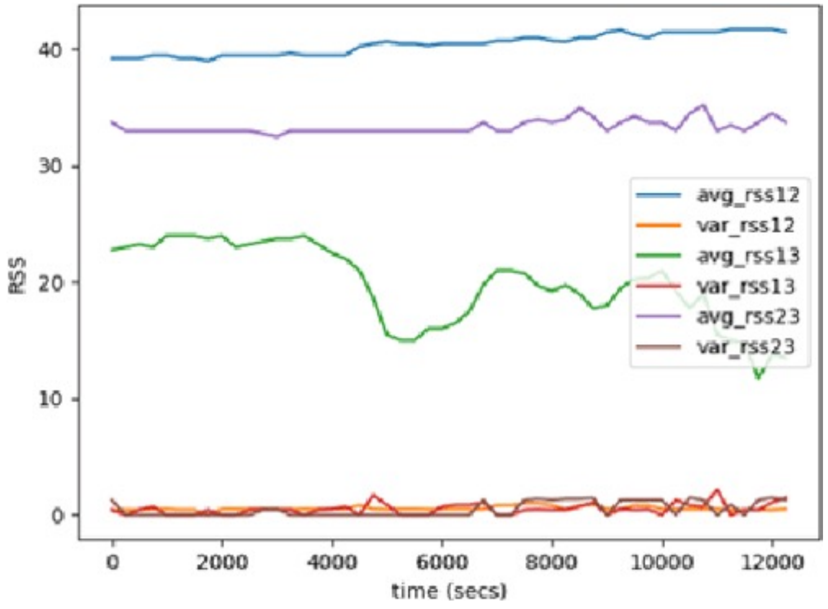
Dataset Description

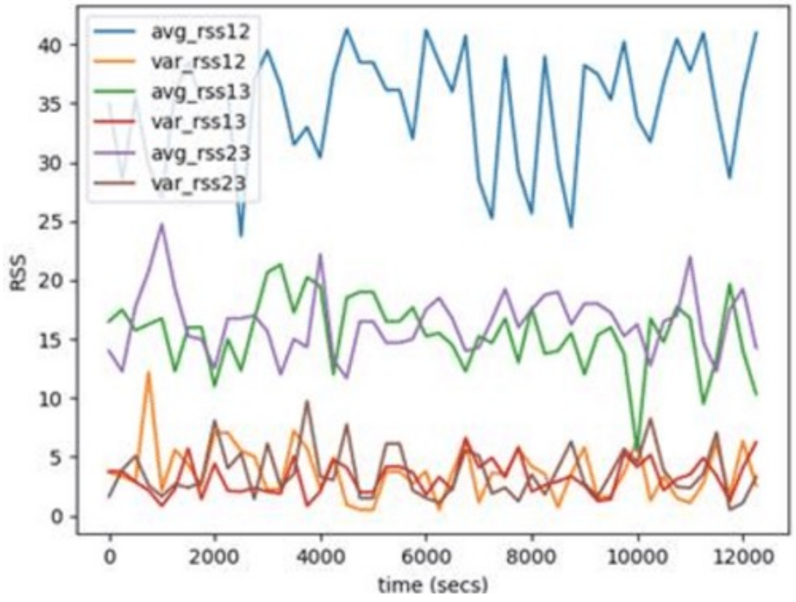
Dataset Characteristics: Multivariate, Sequential, Time-Series
Number of Instances: 42,240
Classes: 7 classes (bending1, bending2, cycling, lying down, sitting, standing, walking)
We consider two kind of bending activity, illustrated in the figure.



Dataset Description

In the AReM dataset, sitting activities demonstrate low variance and stable RSS values, indicating minimal movement, whereas bending activities show high variance and fluctuating RSS values due to dynamic movements and changing orientations.





Research Background

- **Biswas and Samanta** employed the AReM dataset to develop an ensemble random forest model for anomaly detection in wireless sensor networks.
- **Tan et al.** utilized the AReM dataset to implement a many-to-one architecture with GRUs, focusing on elderly activity monitoring. This method achieved an impressive accuracy of 97.14%.
- **Tehrani et al.** explored the AReM dataset alongside others for HAR using Bi-LSTM and reached the accuracy of 95.46%.
- **Yang et al.** focused on enhancing human activity recognition through ensemble learning methods that combine random forests and neural networks. Using the AReM dataset, their approach aimed to improve recognition accuracy by leveraging the strengths of both learning models.

Data Preprocessing

- **Data Loading**
- **Cleaning and Preparation**
- **Feature Standardization**
- **Label Encoding**
- **Sequence Transformation**

Augmentation Techniques

- **Noise Addition:**

  - Integrated controlled noise into the dataset to simulate natural variability in raw sensor data.

  - Aimed to enhance the generalizability of models and mitigate the risk of overfitting.

  - Ensured that models remain robust and accurate for real-world, unseen data scenarios.

- **Time Shifting:**

  - Employed time shifting by randomly adjusting the data by up to five time steps to simulate potential delays or early occurrences in sensor data recording.

  - Enhanced the model's temporal flexibility to better handle real-time data variations.

  - Standardized input dimensions by padding shorter sequences with zeros and trimming longer sequences to 50 time steps.

CNN Model

CNNModel()
├ First Conv1d (conv_layer)
├ Second Conv1d (conv_layer)
├ Third Conv1d (conv_layer)
├ Max Pooling Layer (pool)
├ Fully Connected Layers

The model architecture consists of three convolutional layers followed by max pooling operations. After the convolutional layers, the output is flattened and passed through two fully connected layers. The ReLU activation function is used after each layer except for the output layer.

LSTM Model

LSTMModel()
├ Bidirectional LSTM Layer (lstm)
├ Fully Connected Layers
│ └─Dropout (dropout)

This LSTM architecture, incorporating bidirectional processing, enabling it to capture context from both past and future. It utilizes dropout for regularization and includes two fully connected layers for transforming LSTM outputs into the final desired output dimension.

Transformer Encoder Model

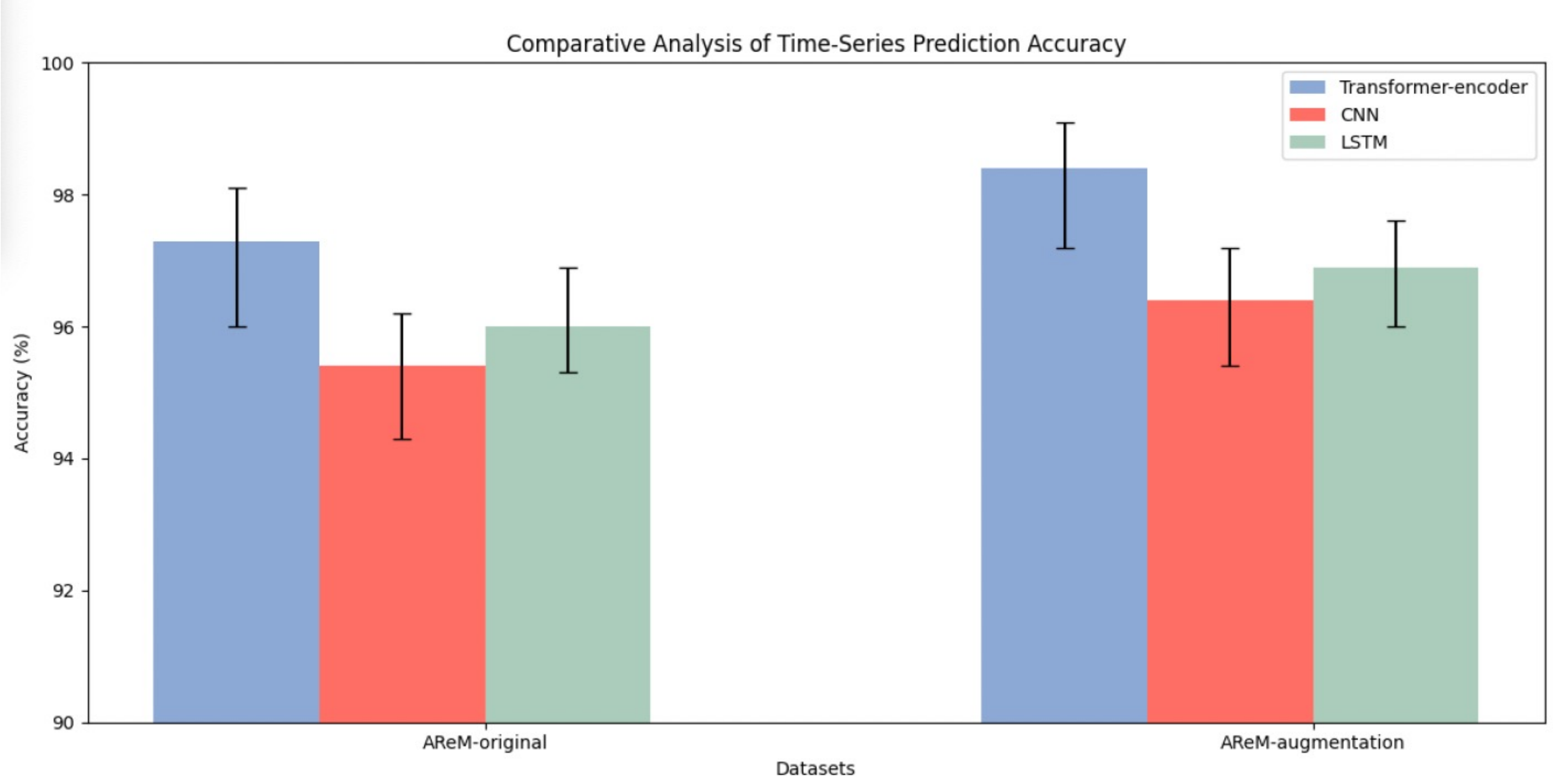
```
TimeSeriesPatchEmbeddingLayer ()
 ├ Conv1d (conv_layer)
 ├ PositionalEncoding (position_embeddings)
 |    └─Dropout (dropout)


TimeSeriesTransformer (TimeSeriesTransformer)
 ├ TimeSeriesPatchEmbeddingLayer ()
 ├ TransformerEncoder (transformer_encoder)
 |    └─ModuleList (layers)
 |    └─TransformerEncoderLayers
```

Results

Table 1. Accuracy in different models and data

Model / Dataset	Transformer		CNN		LSTM	
	Acc.%	95% CI	Acc.%	95% CI	Acc.%	95% CI
AReM-orginal	97.3	[96.0, 98.1]	95.4	[94.3, 96.2]	96.0	[95.2, 96.8]
AReM-augmentation	98.4	[97.2, 99.1	96.4	[95.4, 97.2]	96.9	[95.8, 97.6]



Comparative Analysis of Time-Series Prediction Accuracy
Transformer-encoder
CNN
LSTM
Accuracy (%)
100
98
96
94
92
90
AReM-original
AReM-augmentation
Datasets

Comparing with others

- **Table 1 shows high accuracy for each model across both original and augmented datasets, with the Transformer model on the augmented dataset achieving the best results.**

- **Using the TSAI library, the accuracy recorded was 97.2%, whereas our model achieved an accuracy of 98.4%. This compares favorably to other models, which generally reached around 97% accuracy.**

References:

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