Scalable Hierarchical Deep Neural Network for Time Series Analysis in Wearable Sensor-based Human Activity Recognition

Zahra Ghorrati

Purdue University, West Lafayette, IN 47907, USA
zghorrat@purdue.edu

Abstract

Artificial Intelligence (AI) continues to evolve rapidly, impacting numerous fields, including time series (TS) analysis and human activity recognition (HAR). Despite the advancements in deep learning models, such as Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs), these models face several challenges, including the need for extensive labeled datasets, significant computational resources, and lack of interpretability. This research aims to address these limitations by developing an adaptive hierarchical deep neural network framework that integrates fuzzy logic principles and adaptive learning techniques for robust, computationally efficient, and interpretable real-time TS analysis. The reduction in the number of parameters and the efficient learning of hierarchical features mean that less training data is needed to achieve robust performance. The model's ability to generalize from hierarchical representations allows it to make effective use of smaller datasets, which is particularly advantageous in scenarios where data is limited or expensive to obtain.The proposed framework specifically targets HAR applications using data from wearable sensors.

Introduction

Deep learning (DL) has gained significant attention in Time Series Classification (TSC) due to its pattern recognition capabilities. A survey by (Foumani et al. 2023) and (Fawaz et al. 2019) has comparhensive study on DL model for TSC. (Foumani et al. 2023) categorizes TSC approaches into Multi-Layer Perceptrons (MLPs), Convolutional Neural Networks (CNNs), RNNs, and attention models. While CNNs have seen improvements for TSC, such as Multi-Channel CNNs (Zheng et al. 2014) and Residual Networks (Wang, Yan, and Oates 2017), they often struggle with capturing long-term dependencies. Recent research has expanded beyond traditional models like ResNet, previously the top-performing model as identified by (Fawaz et al. 2019). Transformers and attention-based models, such as InceptionTime (Ismail Fawaz et al. 2020), now outperform ResNet in TSC tasks. Existing TSC and Human Activity Recognition (HAR) models focus on LSTMs, GRUs, and CNNs, which require large labeled datasets and considerable computational resources. These models are generally treated as ”black boxes,” limiting interpretability. Recent hybrid models combining deep learning with Bayesian methods and reinforcement learning have tried to address challenges in time series analysis, but they still lack flexibility for real-time applications. My proposed framework fills these gaps by integrating a hierarchical architecture with fuzzy logic and adaptive deep learning techniques, enhancing both adaptability and interpretability of the model. The core research questions this thesis seeks to address are:

1. Can time series data be classified in a way that ensures interpretability, noise resistance, and scalability using deep neural networks?
2. How can multilevel sensor-based human activity be effectively classified when we have limited data?
3. Can we classify time series data by reducing the input time windows without increasing training complexity?

Proposed Framework

The proposed adaptive hierarchical deep neural network framework consists of several innovative components:

- **Hierarchical Architecture**: The model utilizes a multilevel neural network structure that processes time series data at different temporal resolutions, capturing both short-term and long-term dependencies. This enables the model to recognize complex human activities and predict future states more accurately.
- **Adaptive Learning Mechanism**: The framework integrates an adaptive learning module that adjusts the model's parameters in real-time based on evolving input characteristics. This allows for continuous learning and adaptation without the need for frequent retraining.
- **Fuzzy Logic Integration**: To handle uncertainty and variability in the data, the model incorporates fuzzy logic principles. This approach enhances interpretability by providing more transparent decision-making processes, especially in cases with ambiguous or noisy inputs.
- **Computational Efficiency**: The model is optimized for resource-constrained environments by employing techniques like hierarchical learning. That resulted less training cost These technique ensure the model can be deployed on edge devices, such as smartphones or wearable sensors, for real-time HAR. Hierarchical learning

can reduce the number of parameters that need to be trained in each hirachical level, leading to a decrease in the amount of data required for training. This efficiency arises from the hierarchical structure of models, which organizes learning into layers or levels, each responsible for progressively more abstract representations of the data.

- **Reduced Overfitting:** With fewer parameters to train due to hierarchical learning, the risk of overfitting is diminished. Hierarchical learning mitigates this by focusing on abstracted representations and reducing the complexity of the model.
- **Reduced Need for Random Initialization:** The proposed hierarchical learning approach eliminates the need for random weight initialization because of the convex nature of its objective function. This characteristic contributes to more robust and accelerated convergence during the training process.
- **Robustness to Noise:** The proposed model is robust to noise in the input data. Fuzzy logic systems handle uncertainty and imprecision effectively by defining rules and membership functions. This robustness reduces the sensitivity of the model to noisy inputs, as the fuzzy rules allow for a more flexible and generalized representation of patterns.

Research Progress

Accomplished Work

- **Literature Review and Problem Definition**: The current state-of-the-art methods in TS analysis and HAR is reviewd.
- **Publiction**:Another hierarchical model, which I developed in collaboration with my co-authors, has been applied to TSC and HAR. The details of this work are outlined in the paper accepted for publication, which is listed on my CV.
- **Initial Model Development**: The preliminary version of the hierarchical neural network with fuzzy logic integration is developed.

Remaining Work

- **Model Optimization for Wearable Sensors**: Work is in progress to optimize the framework for real-time HAR using wearable sensor data, with a focus on reducing computational overhead.
- **Implementation of Adaptive Learning Module**: The adaptive learning mechanism will be implemented, allowing the model to adjust its parameters based on the input data's temporal dynamics.
- **Extensive Testing on Real-World Datasets**: The model will be tested on several real-world HAR datasets to evaluate its performance, robustness, and generalization capabilities.

Anticipated Thesis Contributions

The anticipated contributions of this research are:

- **A Novel Adaptive Hierarchical Neural Network Framework**: The proposed framework introduces a unique approach to TS analysis and HAR by combining hierarchical architectures with fuzzy logic and adaptive learning.
- **Improved Accuracy and Interpretability for Real-Time Applications**: By integrating temporal context and fuzzy logic, the framework aims to achieve better performance in recognizing complex human activities while providing more interpretable results.
- **Scalability for Real-World Deployment**: The model's adaptability and computational efficiency make it suitable for deployment on resource-constrained devices, offering practical applications in healthcare, sports analytics, and smart environments.

Conclusion

This research presents a significant advancement in TS analysis and HAR using wearable sensors, providing a robust, adaptive, and interpretable solution for real-time applications. The reduction in the number of parameters and the efficient learning of hierarchical features mean that less training data is needed to achieve robust performance. The model's ability to generalize from hierarchical representations allows it to make effective use of smaller datasets, which is particularly advantageous in scenarios where data is limited or expensive to obtain. Overall, hierarchical learning models that integrate fuzzy rules offer a more robust and efficient approach to training, reducing the dependence on random initialization and improving the handling of noisy data. This combination enhances the model's performance and generalization capabilities. The proposed framework's potential impact spans multiple domains, contributing to the broader field of AI by enabling more accurate and trustworthy decision-making systems

References

Fawaz, H. I.; Forestier, G.; Weber, J.; Idoumghar, L.; and Muller, P.-A. 2019. Deep learning for time series classification: a review. *Data Mining and Knowledge Discovery*, 33(4): 917–963.

Foumani, N. M.; Miller, L.; Tan, C. W.; Webb, G. I.; Forestier, G.; and Salehi, M. 2023. Deep learning for time series classification and extrinsic regression: A current survey. *arXiv preprint arXiv:2302.02515*.

Ismail Fawaz, H.; Lucas, B.; Forestier, G.; Pelletier, C.; Schmidt, D. F.; Weber, J.; Webb, G. I.; Idoumghar, L.; Muller, P.-A.; and Petitjean, F. 2020. Inceptiontime: Finding alexnet for time series classification. *Data Mining and Knowledge Discovery*, 34(6): 1936–1962.

Wang, Z.; Yan, W.; and Oates, T. 2017. Time series classification from scratch with deep neural networks: A strong baseline. In *2017 International joint conference on neural networks (IJCNN)*, 1578–1585. IEEE.

Zheng, Y.; Liu, Q.; Chen, E.; Ge, Y.; and Zhao, J. L. 2014. Time series classification using multi-channels deep convolutional neural networks. In *International conference on web-age information management*, 298–310. Springer.