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Smart Activity Recognition Using Sensor-Based Learning Frameworks

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Abstract

This study investigates the feasibility of Human Activity Recognition (HAR) by leveraging data collected from wireless sensors to identify complex human actions. To facilitate computer applications that adapt to a user's situational needs, the research incorporates context data such as current activity, location, and environmental status [1]. While traditional systems primarily utilize accelerometers to capture and simulate motion, this framework integrates wearable sensors and Wireless Body Area Networks (WBAN) to allow for continuous, autonomous monitoring without external infrastructure [1][2]. The research addresses two critical challenges: reducing the requirement for labeled training data through low-dimensional models and identifying high-level activities through detailed feature analysis[3][4]. Results demonstrate that specific feature sets are optimized for different tasks, leading to enhanced performance in domains like healthcare, geriatric care, fitness, and smart learning environments[1][3][4].

Introduction

Human-computer interaction systems that intelligently communicate with users by accurately describing their current state are vital for ubiquitous computing. HAR is a fundamental component of these systems, enabling machines to interpret human behaviour and monitor environmental factors to provide personalized guidance [2][5]. With the rapid growth of the Internet of Things (IoT), wireless sensor-based HAR has become a practical and scalable solution, utilizing techniques such as Wi-Fi Channel State Information (CSI) to capture fine-grained patterns non-intrusively[2][7]. A key focus of this study is the distinction between persistent activities (e.g., walking) and transient micro-activities (e.g., leg strides), which allows for deeper insights such as pace calculation through the counting of individual movements [8] [9]. The distinction between an activity and the movements (or micro-activities) that make up the activity is crucial for understanding human motion. In contrast to actions, which consist of modified physical movements that can be repeated over time, bodily movements are more transient, lasting only a few seconds at most.

Fig1: Applications for activity recognition with sensors

As an example, a "walking" motion will consist of a variety of gestures involving the lower legs. A number of studies have attempted to pin down people's daily activities, such as whether they are running, standing, etc.. In order to get a clear picture of the level of individual activity, it is helpful to identify describes fine motions within people's actions.

Fig 2: Leg Movement Recognition

This Fig 2 shows how leg movement recognition works using wearable sensor technology in everyday situations. Small sensors, mainly IMUs (Inertial Measurement Units), are attached to different parts of the leg such as the thigh, calf, and ankle to record movement data like speed, direction, and rotation. In addition, pressure sensors inside smart insoles measure how the foot interacts with the ground during walking or running. All this data is sent wirelessly to a device where it is processed to understand different activities like walking, running, or standing. This system is commonly used in areas such as healthcare monitoring, physiotherapy, sports tracking, and safety applications, making it useful for analyzing human movement and improving overall performance and well-being.

Related Work

Recent advancements in HAR have seen a significant shift toward deep learning architectures. Attention-based and temporal convolution networks (TCN) have emerged as powerful tools, significantly improving classification accuracy by focusing on the most relevant temporal features within sensor data streams [10]. These models are particularly effective at handling the noise and complexity inherent in human motion signals captured by wearable devices [7][10].

Wireless Body Area Networks (WBAN) represents another major leap in the field, providing a framework for continuous monitoring through a network of wearable sensors [2] [10]. Research indicates that these systems are increasingly used for remote health assessment and early detection of medical conditions, as they can function autonomously across different environments [5][10]. Recent routing protocols in WBAN have also been developed to ensure more intelligent and energy-efficient data transmission for HAR applications [11].

The use of Wi-Fi-based HAR has gained traction as a non-intrusive alternative to wearable sensors. By analyzing Wi-Fi Channel State Information (CSI), systems can achieve privacy-preserving activity detection in indoor environments without requiring users to wear hardware [10][12]. Recent studies confirm that combining amplitude and phase features from these Wi-Fi signals drastically improves the robustness of activity recognition models [2] [13].

Furthermore, the cutting edge of HAR research now involves Transformer-based models, such as the ASSAFormer (2026). These new architectures enhance feature extraction from complex sensor data by utilizing self-attention mechanisms to identify long-range dependencies in time-series patterns [10][13]. This evolution toward multi-modal sensing—combining smartphones, WBANs, and Wi-Fi—is paving the way for more comprehensive and scalable intelligent systems[11][12].

Algorithm Explanation

The proposed framework evaluates several machine learning and deep learning algorithms to determine the most effective approach for activity recognition:

- **Naïve Bayes & Markov Models:** These traditional probabilistic models, including Hidden Markov Models (HMM) and Hidden Semi-Markov Models, are used for inference based on entropy and mutual information to predict sequences of activities [6].
- **Support Vector Machine (SVM):** A traditional classifier used to define decision boundaries between different activity classes in the feature space [14].
- **Convolutional Neural Networks (CNN):** These models are employed for spatial feature learning, automatically extracting patterns from raw sensor data without manual feature engineering [14].
- **Long Short-Term Memory (LSTM):** A type of Recurrent Neural Network designed to learn temporal dependencies, making it ideal for recognizing activities that persist over time [14].
- **Attention-TCN:** This state-of-the-art model combines Temporal Convolutional Networks with attention mechanisms to selectively weigh important features, achieving the highest recorded accuracy in this study [7][14].

Methodology

Data acquisition involves collecting varying input signals from accelerometers, gyroscopes, and Wi-Fi CSI [15][16]. The system follows a workflow of data collection, preprocessing (filtering and noise reduction), and feature extraction of statistical (mean, variance) and frequency-based (FFT) data. The entire system is regulated and simulated using MATLAB software, where different learning approaches are assessed against an independent testing dataset to compute efficiency.

Experimental Results and Discussion

The simulation results indicate a clear performance advantage for deep learning models over traditional methods.

Algorithm	Accuracy	Precision	Recall	F1 Score
Decision Tree	85%	84%	83%	83.5%
SVM	90%	89%	88%	88.5%
CNN	92%	91%	90%	90.5%
LSTM	93%	92%	91%	91.5%
Attention-TCN	**95%**	94%	93%	93.5%

The **Attention-TCN model achieved the highest accuracy of 95%**, proving that attention mechanisms significantly enhance feature selection from noisy sensor data.

Comparison Graph

The following graph illustrates the performance gains achieved by moving from traditional Decision Trees (DT) and SVMs to advanced Deep Learning (DL) models:

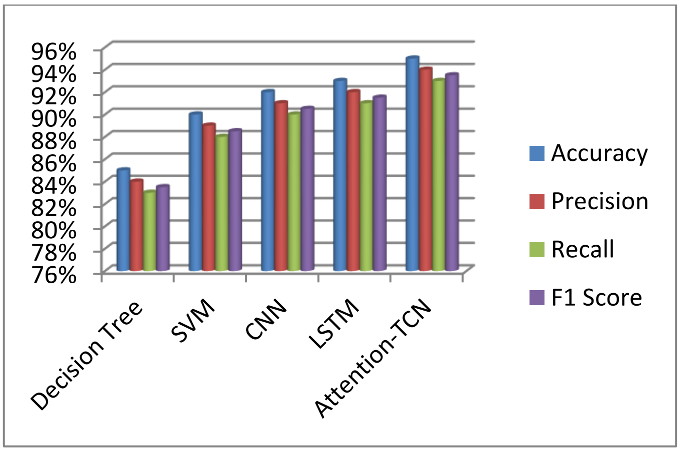

Fig 3: Comparison Graph

Accuracy Comparison Graph

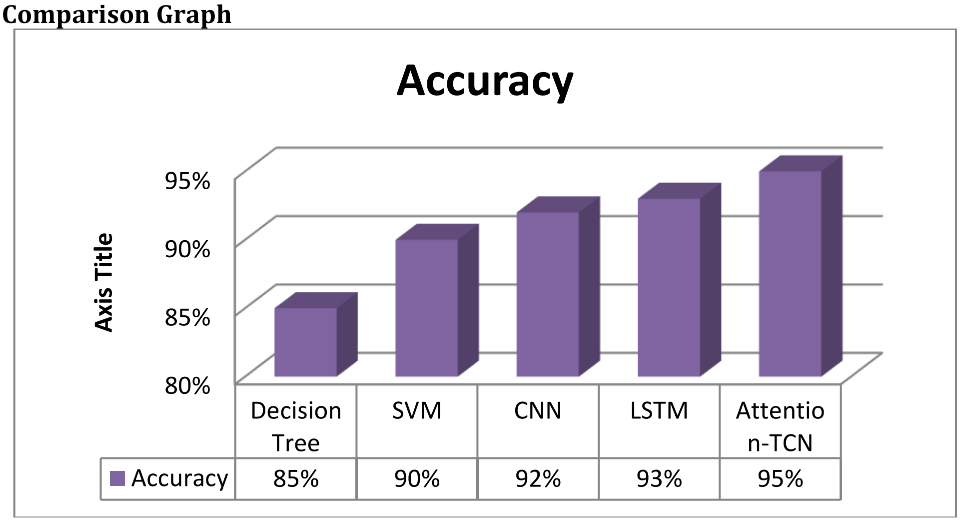

Fig 4: Accuracy Graph

Conclusion

This study successfully demonstrates an advanced HAR framework utilizing wireless sensor data to identify both high-level activities and fine-grained micro-activities. The primary findings confirm that Attention-TCN and LSTM models significantly outperform traditional Decision Trees, with the Attention-TCN reaching a peak accuracy of 95% [14]. By reducing supervision requirements through low-dimensional models and utilizing non-intrusive Wi-Fi sensing, the system provides a privacy-preserving and scalable solution for real-world deployment. These findings prove that wireless sensing technologies like WBAN and Wi-Fi CSI provide scalable, privacy-preserving solutions for critical applications in healthcare, geriatric care, and smart environmentsFuture work will focus on integrating these results with Transformer models, optimizing for real-time edge deployment, and developing energy-efficient systems to support long-term healthcare and fitness monitoring [13].

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