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Human Activity Recognition from Wearable Sensor Data Using Deep Learning

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ABSTRACT

Human activity recognition from wearable sensors underpins many smart-computing applications, including health monitoring, fitness tracking, and ambient assisted living. Recognising activities from inertial sensor signals is challenging because of inter-person variability, sensor noise, and the temporal nature of motion. This paper presents a deep learning approach to human activity recognition that combines convolutional and recurrent layers to learn both local signal features and their temporal evolution from accelerometer and gyroscope data. The model was trained on a labelled dataset of common daily activities and compared with classical and single-architecture deep baselines. The proposed convolutional-recurrent model achieved the highest accuracy at 96.2 percent with a balanced performance across activity classes, outperforming random-forest, convolutional, and recurrent baselines while remaining compact. Per-class analysis showed strong recognition of both static and dynamic activities, with transitional movements proving the most difficult. The results demonstrate that hybrid deep learning on wearable sensor data is an effective and efficient approach to human activity recognition for smart-computing applications.

KEYWORDS: *human activity recognition, wearable sensors, deep learning, convolutional neural network, inertial sensors, ubiquitous computing*

INTRODUCTION

Wearable devices equipped with inertial sensors have become ubiquitous, and the ability to recognise human activities from their signals enables a wide range of smart-computing

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applications, from fitness and health monitoring to assisted living for the elderly (1). Accurate activity recognition turns raw motion signals into meaningful information that systems can act

upon (2).

Recognising activities from accelerometer and gyroscope data is difficult because people perform the same activity differently, sensors introduce noise, and the signals are inherently temporal, with meaning carried by patterns over time. Traditional approaches relied on hand-crafted features and classical classifiers, which require expertise to design and may not generalise well (3). Deep learning can instead learn suitable features directly from the raw signals.

This paper presents a hybrid deep learning model that combines convolutional layers, which extract local features from the sensor signals, with recurrent layers, which model their temporal evolution. The model is trained on a dataset of common daily activities and compared with classical and single-architecture deep baselines using accuracy and per-class metrics (4).

LITERATURE REVIEW

Human activity recognition has moved from feature-engineering pipelines toward end-to-end deep learning, which learns representations directly from sensor data. Convolutional and recurrent architectures, and combinations of the two, have been applied with strong results on benchmark datasets (5).

DEEP LEARNING FOR ACTIVITY RECOGNITION

Convolutional networks are effective at capturing local patterns in sensor windows, while recurrent networks model the temporal dependencies of motion. Studies report that hybrid convolutional-recurrent models combine these strengths and outperform either alone, and that they reduce the need for manual feature design while remaining compact enough for wearable deployment (6).

- Hand-crafted features require expertise and may generalise poorly across people.

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- Convolutional layers extract local features from raw sensor windows.
- Recurrent layers capture the temporal dependencies of human motion.
- Hybrid convolutional-recurrent models combine both strengths effectively.

Even with these advances, many studies report overall accuracy without per-class analysis and do not always compare hybrid models against both classical and single-architecture deep baselines on the same data (7).

RESEARCH GAP

Although deep learning for activity recognition is well studied, evaluations that compare a hybrid convolutional-recurrent model against classical, convolutional, and recurrent baselines on the same data, and that report per-class performance alongside model size, are less common. Balanced recognition across both static and dynamic activities is important yet not always examined (8).

This study addresses the gap by evaluating a hybrid model against three baselines on the same labelled activity dataset and by reporting per-class precision and recall together with model size.

OBJECTIVES

- To prepare a labelled dataset of daily activities from wearable inertial sensors.
- To design a hybrid convolutional-recurrent model for activity recognition.
- To compare the model against classical and single-architecture deep baselines.
- To evaluate per-class performance and model compactness for wearable deployment.

METHODOLOGY

A labelled dataset of common daily activities recorded from body-worn accelerometers and gyroscopes was used to train and evaluate the models. The continuous signals were segmented into fixed windows for classification.

1. Dataset and Sensor Setup

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The composition of the activity dataset is summarised in Table 1. Inertial signals were recorded from multiple subjects performing each activity, and the continuous streams were divided into

overlapping fixed-length windows, each labelled with the activity performed. Signals were normalised before training, and the data were split by subject to test generalisation to unseen people.

Table 1: Activity dataset composition

Activity	Samples	Subjects
Walking	7200	30
Sitting	6000	30
Standing	5800	30
Running	4600	30
Climbing stairs	4200	30

2. Model Architecture and Training

The proposed model passed each sensor window through convolutional layers to extract local features and then through recurrent layers to capture their temporal evolution, followed by a softmax classifier over the activities. It was trained with the Adam optimizer using cross-entropy loss, and the same data splits were used to train a random-forest baseline over hand-crafted features and standalone convolutional and recurrent baselines for comparison.

RESULTS AND FINDINGS

The hybrid model achieved the highest accuracy and balanced per-class performance. Its precision and recall for each activity are shown in Figure 5.

An overall comparison of the hybrid model and the baselines, including accuracy and model size, is given in Table 2.

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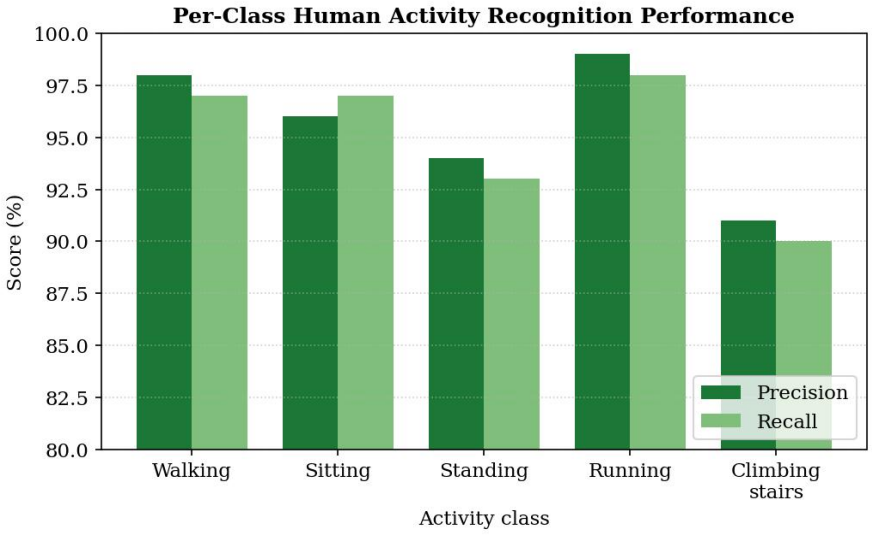

Figure 5: Per-class precision and recall for human activity recognition

As shown in Figure 5, the model recognised both static activities such as sitting and standing and dynamic activities such as walking and running with high precision and recall, with climbing stairs proving the most difficult, though still above ninety percent. As reported in Table 2, the hybrid convolutional-recurrent model reached an overall accuracy of 96.2 percent, ahead of the recurrent, convolutional, and random-forest baselines, while remaining compact at fewer than two million parameters. The balanced per-class results indicate that the model does not favour the more frequent activities.

Table 2: Comparison of evaluated models

Model	Accuracy (%)	F1 (%)	Parameters (M)
Random forest	89.4	88.7	—
Convolutional network	93.6	93.0	1.2
Recurrent network	94.1	93.6	0.9
Hybrid CNN-LSTM (proposed)	96.2	95.8	1.8

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DISCUSSION

The advantage of the hybrid model arises from the complementary roles of its components: the convolutional layers capture the characteristic local shapes of each activity in the sensor signal, while the recurrent layers model how these patterns unfold over time. This combination outperformed both the convolutional and recurrent baselines, confirming that local and temporal information are both important and that learning them jointly is beneficial (9).

The balanced per-class performance is important for real applications, where a system that recognised only common activities would be of limited use. The greater difficulty of transitional movements such as climbing stairs reflects their variability and shorter, less distinct signal patterns. The model's compact size is well suited to deployment on wearable devices, and extending it to a wider range of activities and to data collected in everyday free-living conditions are the natural next steps (10).

CONCLUSION

This paper presented a hybrid convolutional-recurrent deep learning model for human activity recognition from wearable sensor data and showed that it achieved the highest accuracy at 96.2 percent with balanced per-class performance, outperforming random-forest, convolutional, and recurrent baselines while remaining compact. By learning both local signal features and their temporal evolution, the model recognised static and dynamic activities reliably, demonstrating that hybrid deep learning on wearable sensors is an effective and efficient approach for smart-computing applications such as health monitoring and assisted living.

LIMITATIONS

- The dataset covered a limited set of activities recorded under controlled conditions.
- Transitional and overlapping activities were not explicitly modelled.
- Free-living, everyday data with natural activity transitions were not evaluated.

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FUTURE SCOPE

- Extending the model to a broader and finer-grained set of activities.
- Evaluating performance on free-living data collected in everyday conditions.
- Incorporating additional sensor modalities such as heart rate and location.
- Optimising the model for real-time inference on low-power wearable hardware.

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