DeepConvContext: A Multi-Scale Approach to Timeseries Classification in Human Activity Recognition

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Abstract

Despite recognized limitations in modeling long-range temporal dependencies, Human Activity Recognition (HAR) has traditionally relied on a sliding window approach to segment labeled datasets. Deep learning models like the DeepConvLSTM typically classify each window independently, thereby restricting learnable temporal context to within-window information. To address this constraint, we propose DeepConvContext, a multi-scale time series classification framework for HAR. Drawing inspiration from the vision-based Temporal Action Localization community, DeepConvContext models both intra- and inter-window temporal patterns by processing sequences of time-ordered windows. Unlike recent HAR models that incorporate attention mechanisms, DeepConvContext relies solely on LSTMs – with ablation studies demonstrating the superior performance of LSTMs over attention-based variants for modeling inertial sensor data. Across six widely-used HAR benchmarks, DeepConvContext achieves an average 10% improvement in F1-score over the classic DeepConvLSTM, with gains of up to 21%. Code to reproduce our experiments is publicly available via github.com/mariusbock/context_har.

CCS Concepts

• **Human-centered computing → Ubiquitous and mobile computing design and evaluation methods**; • **Computing methodologies → Neural networks**.

Keywords

Human Activity Recognition, Deep Learning, CNN-LSTMs

1 Introduction

Inertial-based Human Activity Recognition (HAR) has, over the past two decades, notoriously relied on a sliding window-based classification approach [7]. Enabling near real-time prediction, this method divides continuous sensor data into overlapping windows, each of which is independently classified by a machine learning model such as the DeepConvLSTM [14]. While subsequent research has sought to enhance models' capabilities through the integration of mechanisms like attention [26] to better model temporal patterns, these models remain fundamentally constrained by their dependence on sliding windows, restricting broader temporal understanding across windows [7].

In 2021, Bock et al. introduced the Shallow DeepConvLSTM [4], a more lightweight version of the DeepConvLSTM that removes the second LSTM layer. While this simplification led to improved performance across multiple HAR benchmark datasets, it also unintentionally introduced a novel form of inter-window learning. Specifically, the model applied the LSTM across windows within a batch, violating the traditional assumption that samples within a batch are independent. Although this design choice was not discussed in the original paper, suggesting it may have been unintentional, the reported results highlight the potential benefits of such cross-window temporal modeling. Similarly, the strategy of processing sequences of time-dependent sliding windows is well-established in a closely related field: single-stage Temporal Action Localization (TAL) [25]. More recently, TAL models have been successfully applied to inertial data and shown to outperform established HAR architectures such as DeepConvLSTM across various datasets [6]. As researchers continue to emphasize the importance of capturing both local and global temporal patterns in HAR [9], this paper introduces DeepConvContext, a novel inertial-based architecture inspired by TAL methodologies, which is is specifically designed to model both short-term (intra-window) and long-term (inter-window) temporal dependencies across sequences of sliding windows.

Our contributions are three-fold:

(1) We propose DeepConvContext, a novel architecture which employs a multi-scale recognition approach capable of capturing temporal dependencies both within and across a series of sliding windows.
(2) An extensive evaluation on six widely-used HAR benchmark datasets, shows that DeepConvContext outperforms both the classical and Shallow DeepConvLSTM architectures, combining strengths of both architectures.
(3) Ablation experiments show that LSTMs are capable of outperforming attention-based techniques by a significant margin, raising the question whether they remain a more suited choice for HAR.

2 Related Work

With the rise of deep learning, researchers have adapted convolutional neural networks (CNNs) for use on time series sensor data, eliminating the need for manual feature extraction that previously relied on domain expert knowledge. In 2016, Ordóñez and Roggen extended this approach by incorporating recurrent layers into inertial-based architectures, enabling them to capture temporal relationships between convolutional features [14]. In their original architecture, Ordóñez and Roggen employed a 2-layered LSTM as their recurrent method of choice. While many researchers have since improved upon the original DeepConvLSTM model [1, 13, 23, 24, 26], the architecture remains a viable and frequently used benchmark for inertial-based human activity recognition. Despite significant progress in improving methods for extracting temporal information, e.g. via including attention-mechanisms

[1, 13, 26], architectures have historically relied on the sliding window approach, where each window of sensor data is processed independently to predict its label. As detailed by Bulling et al. [7], this approach, with its fixed window size, limits the model's ability to capture inter-window temporal dependencies, making the choice of window length a critical factor in HAR performance, with an incorrectly chosen window size resulting in significant performance drops. Recent research has therefore emphasized the need for models that can capture both local and global temporal patterns to overcome the limitations of the sliding window approach [8, 9].

In [16], Pellatt and Roggen propose *CausalBatch*, an improved training method for HAR, where windows within a batch are causally dependent on windows at the same position in neighboring batches. This allows the LSTM states to persist between batches, extending the model's temporal horizon without increasing the window size. Similarly, Hiremath and Ploetz [9] explored the impact of larger context lengths on HAR performance, aggregating convolutional features using larger kernels before passing them through an LSTM. In [20], Shao et al. present an inter- and intra-window learning approach, which learns attention-based features both within and across windows, referred to as *frames* in their work. Compared to [16], our approach introduces a second LSTM specifically designed for learning inter-window context. Following the ideas proposed in [9], we aim to provide our model more flexibility by learning both local and global context separately at the cost of increased model complexity. This approach also aligns with trends in the TAL community, which separates local learning from global timeline reconstruction. In contrast to [20], our model relies on LSTMs, which, as shown in ablation experiments, outperform attention-based techniques.

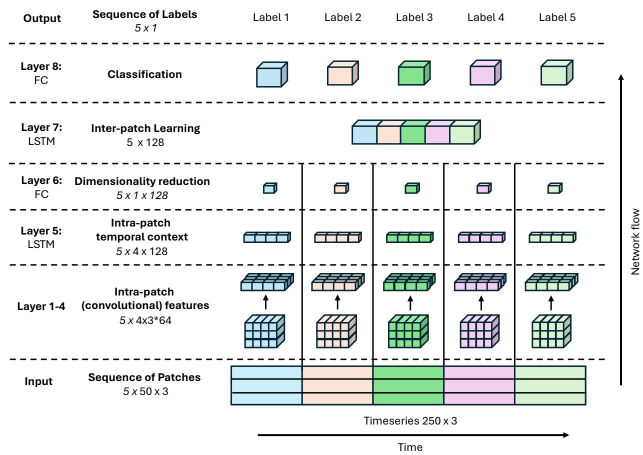

Figure 1: Overview of the proposed *DeepConvContext* architecture. The architecture follows a multi-scale approach in which an input timeseries is segmented into equal-sized patches. These patches are individually processed by a *DeepConvLSTM*-like feature extraction, i.e. a combination of multiple convolution and a LSTM. The resulting intra-patch temporal context vectors are dimensionally reduced to a 1-dimensional feature vector. The sequence of feature vectors of all patches are then passed to a second LSTM, to learn inter-patch temporal features. Resulting patch-wise feature vectors are then classified and a sequence of patch-wise activity labels is returned.

3 Methodology

3.1 Architecture Overview

Figure 1 illustrates the data flow of the proposed DeepConvContext architecture. This architecture follows a multi-scale approach, incorporating methods for extracting temporal features from inertial sensor time series, inspired by both the original [14] and Shallow DeepConvLSTM [4]. Given a multivariate time series from a set of inertial sensor axes, DeepConvContext begins by segmenting the sequence into equal-sized patches using a sliding-window approach. Features are extracted from each patch through multiple convolutional layers, followed by an LSTM, which mirrors the feature extraction process of the original DeepConvLSTM. This stage is designed to capture discriminative temporal dependencies within each sliding window. Unlike the original DeepConvLSTM, which performs classification based on the final element of each patch, DeepConvContext introduces an additional stage that captures dependencies across patches. This inter-patch learning mechanism is inspired by the design of the Shallow DeepConvLSTM. To achieve this, each patch is reduced to a one-dimensional feature vector of size $1 \times LSTM_h$, where $LSTM_h$ represents the number of hidden units in the last layer of the intra-patch LSTM. These patch representations are then treated as a new sequential input to a second LSTM, which models temporal dependencies across patches. The output of this second LSTM is passed through a dropout layer and a fully connected classification layer. Because each patch is processed by both intra- and inter-patch LSTMs, it retains information about its internal temporal structure, as well as its temporal relationship with earlier patches in the sequence.

3.2 Datasets

We base our experiments on six widely used HAR datasets. These include the Wetlab [19], WEAR [5], SBHAR [17], RWHAR [21], Opportunity [18], and Hang-Time datasets [10]. This selection provides a diverse set of prediction scenarios, each posing distinct challenges for activity recognition models to address. Among these challenges are variations in the number of participants and activity classes, the presence of a NULL-class [5, 10, 18, 19], and the inclusion of complex, short-duration, transitional, and locomotion activities [5, 10, 17–19, 21]. Additionally, the datasets vary in sensor configurations, with several collected in multi-sensor environments [5, 18, 21].

3.3 Architecture Variants

By default, LSTMs operate in an unidirectional manner, processing input sequences from past to present. Within the DeepConvContext architecture, this means that patches, i.e. windows, are fed sequentially into the model, with the first patch corresponding to the earliest time point and each subsequent patch representing the next point in time. This design limits the LSTM to only past and present information, preventing it from incorporating any future context into its predictions. However, certain activities, such as *sit-to-stand* present in the SBHAR dataset [17], can benefit from access to future context during prediction. To address this, we also evaluate a variant of the DeepConvContext that uses a bidirectional LSTM to model inter-patch temporal dependencies. In this variant, the second LSTM within the DeepConvContext module (depicted in Figure 1) processes each batch sequence in both forward and backward temporal directions. For every patch, it outputs two vectors of size $1 \times LSTM_h$, where $LSTM_h$ is the number of hidden units in the LSTM. These vectors are then concatenated to form a combined representation, which is passed, just like in the unidirectional case, into a fully connected layer that serves as the classifier.

LSTMs, though effective at modeling local temporal dependencies, often struggle to learn long-range relationships when the temporal distance between relevant sequence elements increases [2, 15]. In contrast, self-attention mechanisms can capture dependencies between all elements of a sequence, regardless of their relative position in time. While this capability comes with increased computational overhead, it has led to notable performance gains in inertial sensor-based architectures such as Attend-and-Discriminate [1] and TinyHAR [26]. In line with these developments, we further evaluate two additional variants of the DeepConvContext architecture: one using multi-head self-attention and another incorporating a transformer module, as described in [12]. To maintain consistency with the LSTM-based setups, we implement unidirectional versions of both attention-based mechanisms, specifically, causal attention and causal transformers, to ensure that each model only learns from past temporal information.

3.4 Training

For each experiment, we perform Leave-One-Subject-Out (LOSO) cross-validation, where each participant in the dataset is used as the validation set once, while all other participants are used for training. We report two key metrics for each experiment: the class-averaged macro F1-score and the mean Average Precision (mAP), both averaged across all validation splits (i.e., participants). The mAP, which evaluates the overlap between predicted activity segments and ground truth annotations, is computed across five different temporal Intersection-over-Union (tIoU) thresholds. To calculate both mAP and F1-score, we first convert the windowed predictions of each model back to per-sample predictions by unwindowing them. This ensures that both metrics are computed on the same temporal resolution. The final reported values per dataset are the averages of the tIoU-averaged mAP and class-averaged F1-score across all validation subjects. All model architectures are trained using a weighted cross-entropy loss and the Adam optimizer, with a learning rate of $1e^{-4}$, weight decay of $1e^{-6}$. Each model is trained for 30 epochs, using a learning rate schedule that multiplies the learning rate by a factor of 0.9 every 10 epochs. A training batch size of 100 is used for all experiments. For evaluation, the original DeepConvLSTM is tested using a batch size of 1, while models that rely on inter-window features, namely the Shallow DeepConvLSTM and DeepConvContext, are evaluated with a test batch size equal to the training batch size (100), to maintain the temporal structure required for inter-window learning. All architectures evaluated in this benchmark use four convolutional layers with 64 filters, each of size 9×1, except for the Opportunity dataset, where a smaller filter size of 5×1 is used due to the lower sampling rate of the input signal. LSTM layers are configured with a hidden size of 128 and no dropout between layers. In ablation experiments where LSTMs are replaced with transformers or multi-head self-attention mechanisms, we use four attention heads with no dropout. The transformer-based variants use three layers. Same as Ordóñez and Roggen [14], embeddings get passed through a dropout layer with a probability of 0.5 before being passed to the classifier.

4 Results

4.1 Benchmark analysis

In Figure 2, we present an overview of the results for the classic DeepConvLSTM [14], the Shallow DeepConvLSTM [4], and the proposed DeepConvContext model, all using a single LSTM layer per module. On average, the multi-scale DeepConvContext achieves the highest prediction performance, with an average F1-score of 59.04%, compared to 49.09% for the intra-window DeepConvLSTM and 54.01% for the inter-window Shallow DeepConvLSTM, across the six evaluated datasets. When comparing the intra-and inter-window models, we observe that the inter-window DeepConvLSTM struggles to produce coherent activity segments, reflected by its average mAP being close to zero across all datasets. In contrast, both the Shallow DeepConvLSTM and DeepConvContext leverage temporal relationships across windows and thus produce fewer rapid switches between activities, achieving significantly higher average mAP values of 16.79 and 18.23, respectively. It is worth noting that the RWHAR dataset does not include a NULL class and contains only a single segment per activity per participant. This makes mAP evaluation particularly sensitive, since the metric is biased toward zero unless a model predicts an activity nearly perfectly across its full duration in the participant's data stream.

The Shallow DeepConvLSTM outperforms the classical DeepConvLSTM on all datasets except Opportunity. This highlights the importance of inter-window context for accurate activity recognition, as the Shallow DeepConvLSTM does so by only relating convolutional features of the final sequence element from each window in a batch. It is capable of recognizing both periodic activities such as *sitting* (found in datasets like SBHAR and RWHAR) and non-periodic or transitional activities such as *sit-to-lie* in SBHAR. However, as shown in the confusion matrices in Figure 3, the DeepConvLSTM still outperforms the Shallow DeepConvLSTM for strictly periodic activities. This is likely because such activities are often characterized by short, repeating patterns that can be effectively captured by convolutional filters and do not require modeling of long-range temporal dependencies [3]. Understanding this, the DeepConvContext effectively combines the strengths of both intra- and inter-window learning, maintaining high predictive performance on all activity types. Finally, Figures 2 and 3 also show the results for a variant of DeepConvContext that uses a bidirectional LSTM for inter-window learning. By incorporating information from future windows, this variant improves the accuracy of predictions for individual windows and leads to a substantial increase in overall mAP.

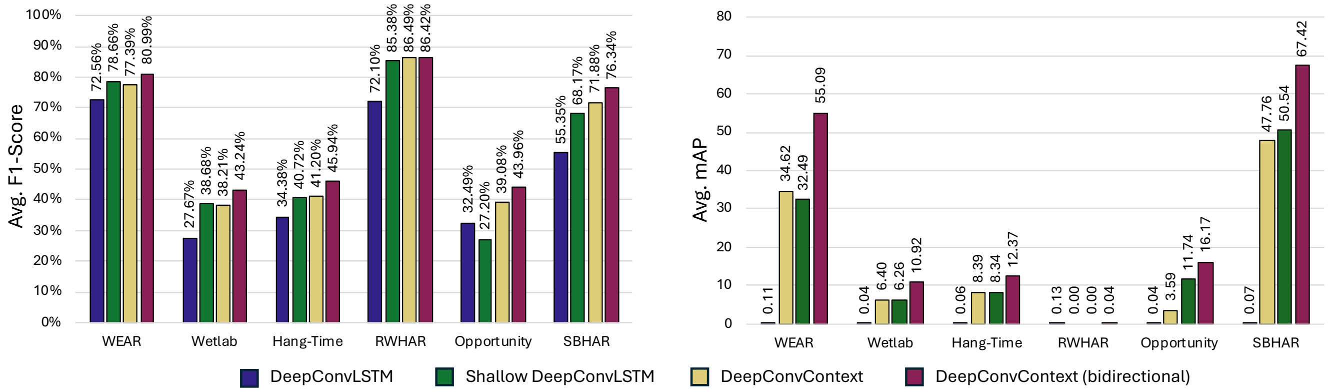

Figure 2: Average F1-score and mAP results of the DeepConvLSTM [14], Shallow DeepConvLSTM [4] and proposed DeepConvContext being applied to the WEAR [5], Wetlab [19], Hang-Time [10], RWHAR [21], Opportunity [18] and SBHAR [17]. The DeepConvContext is additionally evaluated using bidirectional LSTM to perform inter-window learning. Results are the class- and participant-averaged scores averaged across three runs using different random seeds. One can see that the DeepConvContext combines strengths of both architectures and improves upon results across all datasets, with the bidirectional version of the architecture providing the highest F1-score and mAP.

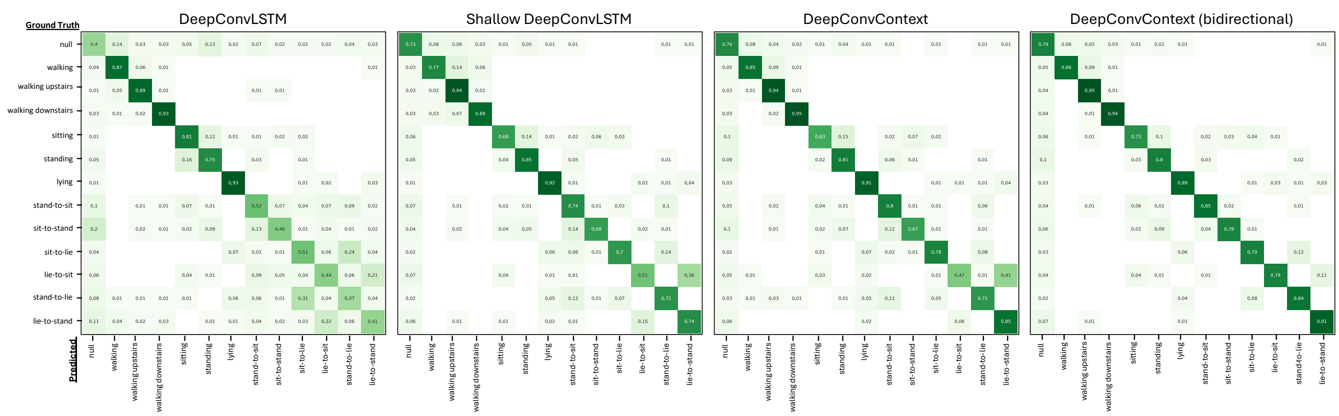

Figure 3: Per-class confusion matrices of the DeepConvLSTM, Shallow DeepConvLSTM and DeepConvContext being applied to the SBHAR dataset using LOSO cross-validation. The DeepConvContext is further applied using bidirectional LSTM as described in Chapter 3.3. One can see that the DeepConvContext improves upon both variants of the DeepConvLSTM, with the bidirectional variant producing the overall highest prediction results. Especially transition classes such as *sit-to-stand* are more reliably detected.

4.2 Ablation experiments

Revisiting shallow LSTMs. When introducing the Shallow DeepConvLSTM in [4], Bock et al. demonstrated that shallow LSTMs might be a better option for inertial-based activity recognition, challenging the widely held belief based on the earlier findings of Karpathy et al. [11]. However, since the original Shallow DeepConvLSTM paper unintentionally focussed on the use of LSTMs for learning inter-window features, their analysis does not provide evidence to conclude that shallow LSTMs are superior for learning intra-window dependencies. To revisit this claim, we conducted a comparative evaluation using the original DeepConvLSTM, the Shallow DeepConvLSTM, and our proposed DeepConvContext model. Each architecture was tested with both single-layer and two-layer LSTM configurations. As shown in Table 1, the results indicate that single-layer LSTMs tend to outperform their two-layer counterparts across all datasets, with the exception of the Opportunity dataset [18]. Moreover, the performance gains from using shallower LSTMs are more significant when applied to inter-window learning. We attribute this due to the longer inter-window sequences likely containing a richer set of learnable patterns than intra-window sequences, which may make the limitations of deeper LSTMs more evident and highlight the advantages of shallow 1-layered variants.

LSTMs vs. Attention. With the rise in popularity of attention-based mechanisms, architectures such as those proposed in [1]

Table 1: Average F1-score results of the DeepConvLSTM [14] (DC-LSTM), Shallow DeepConvLSTM [4] (Shallow D.) and proposed DeepConvContext using either 1-layered (1-L) or 2-layered LSTMs (2-L) within the architectures. We report results for the WEAR [5], Wetlab [19], Hang-Time [10], RWHAR [21], Opportunity [18] and SBHAR [17]. Results are the class- and participant-averaged scores averaged across three runs using different random seeds. One can see that one-layered LSTMs outperform 2-layered LSTMs across all architectures and datasets, except the Opportunity dataset. Best results per dataset are underlined.

D	DC-LSTM		Shallow D.		DeepConvContext	
	1-L	2-L	1-L	2-L	1-L	2-L
[5]	72.56%	70.04%	78.66%	74.27%	77.39%	75.12%
[19]	27.67%	26.26%	38.68%	33.64%	38.21%	33.61%
[10]	34.38%	33.76%	40.72%	38.24%	41.20%	39.80%
[21]	72.10%	70.90%	85.38%	83.36%	86.49%	84.42%
[18]	32.49%	37.66%	27.20%	31.03%	39.08%	33.39%
[17]	55.35%	54.37%	68.17%	63.50%	71.88%	61.03%
Avg	*49.09%*	*48.83%*	*56.47%*	*54.01%*	*59.04%*	*54.56%*

Table 2: Comparison of average F1-score results of the DeepConvContext using either an LSTM, attention or a Transformer to learn inter-window context. We assess both unidirectional and bidirectional versions of the three techniques. We report results for the WEAR [5], Wetlab [19], Hang-Time [10], RWHAR [21], Opportunity [18] and SBHAR [17]. Results are the class- and participant-averaged scores averaged across three runs using different random seeds. One can see that on average LSTMs outperform both attention and Transformers. Best unidirectional and bidirectional results per dataset are underlined.

D	Unidirectional			Bidirectional		
	LSTM	Att.	Tran.	LSTM	Att.	Tran.
[5]	77.39%	76.21%	76.15%	80.99%	80.25%	75.34%
[19]	38.21%	31.64%	28.81%	43.24%	37.45%	28.03%
[10]	41.20%	38.44%	37.85%	45.94%	42.45%	36.62%
[21]	86.49%	86.59%	63.60%	86.42%	89.71%	62.14%
[18]	39.08%	36.68%	38.96%	43.96%	32.36%	33.79%
[17]	71.88%	67.43%	75.65%	76.34%	71.25%	76.15%
Avg	*59.04%*	*56.17%*	*53.50%*	*62.82%*	*58.91%*	*52.01%*

have demonstrated their applicability to HAR. However, as previous studies have primarily focused on architectures designed to learn intra-window features, we conducted further experiments to investigate whether multi-head attention [22] and ViT-style Transformers [12] could serve as more effective alternatives to LSTMs for modeling temporal dependencies between windows. To explore this question, and as described in Section 3.3, we replaced the second LSTM in the DeepConvContext architecture with either a multi-head attention block or a Transformer module. As shown in Table 2, our results indicate that LSTMs outperform attention-based mechanisms across the selected benchmark datasets. In particular, for the Wetlab and Hang-Time datasets, LSTMs achieve an average F1-score that is approximately 10% higher than that of the Transformer-based variants. While attention mechanisms allow features to interact across the entire input sequence, they typically exhibit a reduced sensitivity to the natural order of events in time and rely on positional encodings to provide temporal structure. Although we included such encodings in our models, the relatively lower performance of the attention-based variants suggests that LSTMs may be more effective at capturing temporal relationships among windows. Since many human activities do not require excessively long temporal contexts for accurate classification, LSTMs may be better suited for such HAR tasks due to their strength in modeling localized temporal patterns. This assumption is further supported by the improved performance of attention-based DeepConvContext variants on the RWHAR and SBHAR datasets. In these cases, the long and sequential nature of activity segments allows attention layers to learn extended temporal dependencies more effectively. These dependencies enable the model to reproduce the long, coherent activity sequences present in the data patterns, which LSTMs may struggle to model as efficiently.

5 Limitations

The DeepConvContext architecture presents a novel approach to processing inertial sensor data for activity recognition. Although not specifically tested within this work, its architectural design choices can be readily extended to other inertial-based models such as TinyHAR [26] and Attend-and-Discriminate [1]. While our analysis evaluates only modified versions of the original DeepConvLSTM, we expect the observed performance improvements to generalize to other architectures, as they follow a common design pattern of combining convolutional feature extraction with some form of temporal modeling. Compared to CausalBatch [16] as well as related work [9], our architecture introduces some additional computational complexity, as shown in Table 3. However, by incorporating a projection layer between the two LSTMs, the overall increase in GPU memory usage and floating point operations remains modest, being approximately 3.5% and 10%, respectively. Furthermore, while Table 3 indicates that the attention-based version of DeepConvContext uses fewer learnable parameters, LSTMs are slightly more computational efficient. In our experiments, we did not modify the data loading strategy of the evaluated HAR datasets, apart from disabling batch shuffling to maintain temporal consistency among batch elements. This consistency is essential, and the same principle must be applied during testing. For instance, using a test batch size of 1 would prevent the model from accessing any contextual information across patches, thereby negating the benefits of inter-window learning. In real-world applications, this constraint means that DeepConvContext cannot be directly applied in an online setting. Instead, it requires data to be collected for a duration of $b \times (w - o)$ seconds, where b is the training batch size, w is the sliding window length in seconds, and o is the overlap in seconds. This makes the context length a hyperparameter which needs to be considered during training of a network as it influences recognition of activities (see Table 4). Future research could focus on designing an optimized data loader that maintains a running

Table 3: Model complexity of the original DeepConvLSTM (DC-LSTM), Shallow DeepConvLSTM (Shallow D.) and architecture variants of the DeepConvContext (DCC) in terms of number of learnable parameters (ρ), GigaFLOPS (GFLOPS) and GPU memory consumption (Memory). All architectures apply 1-layered LSTMs, if applicable. Attention-based architectures use 4 attention heads as well as 3 Transformer layers. One can see that the DeepConvContext has around 2.5 times more learnable parameters, yet only introduces a 3.5% and 10% increase in GFLOPS and memory consumption.

Architecture	ρ	MFLOPS	Memory
DC-LSTM	277,062	1,739.98	114.42MB
Shallow D.	277,062	1,739.98	114.42MB
DCC (LSTM)	704,198	1,798.96	124.21MB
DCC (Bi-LSTM)	837,062	1,799.19	128.09MB
DCC (Att.)	638,150	1,817.22	123.20MB
DCC (Tran.)	1,961,158	2,074.42	143.39MB

Table 4: Average F1-score and mAP results of the DeepConvContext using varying train and test batch sizes (25, 50 and 200). We report results for the WEAR [5], Wetlab [19], Hang-Time [10], RWHAR [21], Opportunity [18] and SBHAR [17]. Results are the class- and participant-averaged scores averaged across three runs using different random seeds. One can see that on average LSTMs outperform both attention and Transformers.

D	25		50		200	
	F1	mAP	F1	mAP	F1	mAP
[5]	74.25%	22.81	76.44%	26.02	78.37%	37.44
[19]	30.57%	1.83	35.35%	4.01	38.32%	6.78
[10]	40.00%	7.66	40.44%	8.32	41.73%	8.72
[21]	50.23%	0.02	84.09%	0.06	85.68%	0.00
[18]	31.04%	6.26	34.68%	7.81	39.28%	10.84
[17]	66.46%	38.08	68.25%	44.48	74.64%	55.66
Avg	*48.76*	*12.78*	*56.54*	*15.12*	*59.67*	*19.91*

memory of previously seen windows. This would enable the architecture to function according to a first-in, first-out (FIFO) principle, where features are computed only for the newly recorded window and then related to past context. Such a strategy would allow for an efficient and online deployment of the DeepConvContext architecture. Alternatively, one could extend the data loading process by extending the sliding window input to a context dimension of previously recorded data. This would allow for shuffling batch elements, possibly resulting in improved results as architectures would be optimised on alternating contexts and activities.

6 Discussion & Conclusions

In this paper we introduced DeepConvContext, a novel architecture for inertial-based activity recognition. Inspired by advancements in the vision-based Temporal Action Localization community, the architecture adopts a multi-scale approach that learns both intra- and inter-window temporal dependencies to predict the label of a given sliding window. Our analysis revealed that although this was not discussed in the original publication, the Shallow DeepConvLSTM [4] introduced a unique method for learning inter-window temporal features by implicitly relating windows within a batch. While this approach challenges the conventional definition of a batch, our results highlight the importance of inter-window learning. Benchmark experiments showed that inter-window learning consistently outperforms intra-window learning, as used in the original DeepConvLSTM [14], across a range of Human Activity Recognition datasets. DeepConvContext builds on the strengths of both prior architectures by integrating both intra- and inter-window learning into a single unified model. Our benchmark analysis showed that on average, our architecture outperforms both the original and Shallow DeepConvLSTM, with gains up to 21% in F1-score. Further ablation experiments, which involved testing architectural variants of DeepConvContext, demonstrated that average mAP can be significantly improved by making the second LSTM, which is responsible for inter-window learning, bidirectional. Additional experiments showed that LSTMs are more effective than attention-based mechanisms, raising the question of whether their strong focus on local temporal structures makes them better suited for recognizing human activities, which often do not require long range temporal connections.

With DeepConvContext, we present the HAR community with a novel method for processing windowed data and predicting activity labels. We directly address the well-known sliding window problem [7] and align with the community's ongoing efforts to overcome it [9, 16]. Although our current implementation does not yet incorporate an optimized multi-scale batch data loader, we consider this a promising direction for future research and expect it to further enhance the performance of our architecture. With our suggested changes being easily extendable to other architectures, we hope that our proposed multi-scale approach will become an essential component within future works.

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References

[1] Alireza Abedin, Mahsa Ehsanpour, Qinfeng Shi, Hamid Rezatofighi, and Damith C. Ranasinghe. 2021. Attend and Discriminate: Beyond the State-Of-The-Art for Human Activity Recognition Using Wearable Sensors. *ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 5, 1 (2021), 1–22. doi:10.1145/3448083

[2] Y. Bengio, P. Simard, and P. Frasconi. 1994. Learning Long-Term Dependencies with Gradient Descent Is Difficult. *IEEE Transactions on Neural Networks* 5, 2 (1994), 157–166. doi:10.1109/72.279181

[3] Marius Bock, Alexander Hoelzemann, Michael Moeller, and Kristof Van Laerhoven. 2022. Investigating (Re)Current State-of-the-Art in Human Activity Recognition Datasets. *Frontiers in Computer Science* 4 (2022), 924954. doi:10.3389/fcomp.2022.924954

[4] Marius Bock, Alexander Hölzemann, Michael Moeller, and Kristof Van Laerhoven. 2021. Improving Deep Learning for HAR with Shallow LSTMs. In *Proceedings of the 2021 ACM International Symposium on Wearable Computers*. doi:10.1145/3460421.3480419

[5] Marius Bock, Hilde Kuehne, Kristof Van Laerhoven, and Michael Moeller. 2024. WEAR: An Outdoor Sports Dataset for Wearable and Egocentric Activity Recognition. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 4 (2024), 1–21. doi:10.1145/3699776

[6] Marius Bock, Michael Moeller, and Kristof Van Laerhoven. 2024. Temporal Action Localization for Inertial-based Human Activity Recognition. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 4 (2024). doi:10.1145/3699770

[7] Andreas Bulling, Ulf Blanke, and Bernt Schiele. 2014. A Tutorial on Human Activity Recognition Using Body-Worn Inertial Sensors. *Comput. Surveys* 46, 3 (2014), 1–33. doi:10.1145/2499621

[8] Nils Y. Hammerla and Thomas Plötz. 2015. Let's (Not) Stick Together: Pairwise Similarity Biases Cross-Validation in Activity Recognition. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15)*. Association for Computing Machinery, Osaka, Japan and New York, NY, USA, 1041–1051. doi:10.1145/2750858.2807551

[9] Shruthi Kashinath Hiremath and Thomas Ploetz. 2021. On the Role of Context Length for Feature Extraction and Sequence Modeling in Human Activity Recognition. In *2021 International Symposium on Wearable Computers*. ACM, Virtual USA, 13–17. doi:10.1145/3460421.3478825

[10] Alexander Hoelzemann, Julia Lee Romero, Marius Bock, Kristof Van Laerhoven, and Qin Lv. 2023. Hang-Time HAR: A Benchmark Dataset for Basketball Activity Recognition Using Wrist-Worn Inertial Sensors. *Sensors* 23, 13 (2023). doi:10.3390/s23135879

[11] Andrej Karpathy, Justin Johnson, and Fei-Fei Li. 2015. Visualizing and Understanding Recurrent Networks. *CoRR* abs/1506.02078 (2015). doi:10.48550/arXiv.1506.02078

[12] Alexander Kolesnikov, Alexey Dosovitskiy, Dirk Weissenborn, Georg Heigold, Jakob Uszkoreit, Lucas Beyer, Matthias Minderer, Mostafa Dehghani, Neil Houlsby, Sylvain Gelly, Thomas Unterthiner, and Xiaohua Zhai. 2021. An Image Is Worth 16x16 Words: Transformers for Image Recognition at Scale. In *Ninth International Conference on Learning Representations*. doi:10.48550/arXiv.2010.11929

[13] Vishvak S. Murahari and Thomas Plötz. 2018. On Attention Models for Human Activity Recognition. In *ACM International Symposium on Wearable Computers*. doi:10.1145/3267242.3267287

[14] Francisco Javier Ordóñez and Daniel Roggen. 2016. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition. *MDPI Sensors* 16, 1 (2016). doi:10.3390/s16010115

[15] Razvan Pascanu, Tomas Mikolov, and Yoshua Bengio. 2013. On the Difficulty of Training Recurrent Neural Networks. In *Proceedings of the 30th International Conference on Machine Learning (Proceedings of Machine Learning Research, Vol. 28)*, Sanjoy Dasgupta and David McAllester (Eds.). PMLR, Atlanta, Georgia, USA, 1310–1318. https://proceedings.mlr.press/v28/pascanu13.html

[16] Lloyd Pellatt and Daniel Roggen. 2020. CausalBatch: Solving Complexity/Performance Tradeoffs for Deep Convolutional and Lstm Networks for Wearable Activity Recognition. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing and ACM International Symposium on Wearable Computers*. doi:10.1145/3410530.3414365

[17] Jorge-L. Reyes-Ortiz, Luca Oneto, Albert Samà, Xavier Parra, and Davide Anguita. 2016. Transition-Aware Human Activity Recognition Using Smartphones. *Neurocomputing* 171 (2016). doi:10.1016/j.neucom.2015.07.085

[18] Daniel Roggen, Alberto Calatroni, Mirco Rossi, Thomas Holleczek, Kilian Förster, Gerhard Tröster, Paul Lukowicz, David Bannach, Gerald Pirkl, Alois Ferscha, Jakob Doppler, Clemens Holzmann, Marc Kurz, Gerald Holl, Ricardo Chavarriaga, Hesam Sagha, Hamidreza Bayati, Marco Creatura, and José del R. Millàn. 2010. Collecting Complex Activity Datasets in Highly Rich Networked Sensor Environments. In *IEEE Seventh International Conference on Networked Sensing Systems*. doi:10.1109/INSS.2010.5573462

[19] Philipp M. Scholl, Matthias Wille, and Kristof Van Laerhoven. 2015. Wearables in the Wet Lab: A Laboratory System for Capturing and Guiding Experiments. In *ACM International Joint Conference on Pervasive and Ubiquitous Computing*. doi:10.1145/2750858.2807547

[20] Shuai Shao, Yu Guan, and Victor Sanchez. 2024. Beyond Isolated Frames: Enhancing Sensor-Based Human Activity Recognition through Intra- and Inter-Frame Attention. doi:10.48550/arXiv.2405.19349 arXiv:2405.19349 [eess]

[21] Timo Sztyler and Heiner Stuckenschmidt. 2016. On-Body Localization of Wearable Devices: An Investigation of Position-Aware Activity Recognition. In *IEEE International Conference on Pervasive Computing and Communications*. doi:10.1109/PERCOM.2016.7456521

[22] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention Is All You Need. In *Advances in Neural Information Processing Systems*. doi:10.48550/arXiv.1706.03762

[23] Rui Xi, Mengshu Hou, Mingsheng Fu, Hong Qu, and Daibo Liu. 2018. Deep Dilated Convolution on Multimodality Time Series for Human Activity Recognition. In *IEEE International Joint Conference on Neural Networks*. doi:10.1109/IJCNN.2018.8489540

[24] Cheng Xu, Duo Chai, Jie He, Xiaotong Zhang, and Shihong Duan. 2019. InnoHAR: A Deep Neural Network for Complex Human Activity Recognition. *IEEE Access* 7 (2019). doi:10.1109/ACCESS.2018.2890675

[25] Chen-Lin Zhang, Jianxin Wu, and Yin Li. 2022. Actionformer: Localizing Moments of Actions With Transformers. In *European Conference on Computer Vision*. doi:10.1007/978-3-031-19772-7_29

[26] Yexu Zhou, Haibin Zhao, Yiran Huang, Till Riedel, Michael Hefenbrock, and Michael Beigl. 2022. TinyHAR: A Lightweight Deep Learning Model Designed for Human Activity Recognition. In *ACM International Symposium on Wearable Computers*. doi:10.1145/3544794.3558467