# A Hierarchical Machine Learning Framework for Military Activity Recognition

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## Summary

Human activity recognition (HAR) systems can help automatically identify movement patterns performed by military members, improving the military's ability to investigate movement-specific biomechanical outcomes. However, the accuracy of deep-learning methods for temporal data is limited by window and step sizes. We propose a hierarchical machine-learning framework to improve the classification accuracy of military tasks. Our framework's performance was compared to a deep convolutional long-short-term memory neural network (ConvLSTM). The hierarchical framework achieved higher accuracy and subsequence performance than the ConvLSTM model.

## Introduction

Accurately labelling complex movements recorded as part of prolonged military training exercises is crucial for optimising and monitoring military task performance. Furthermore, segmenting sub-movements from large datasets of motion data enables military researchers to perform in-depth movement-specific assessments. Traditional methods, such as capturing movements in isolation or manually identifying movements within larger datasets, reduce ecological validity and are time-consuming. HAR systems offer an alternative by leveraging deep-learning models to classify movement patterns within large datasets using overlapping sliding windows. Military HAR models have previously been developed using a ConvLSTM model with data from a single IMU [1]. However, the model's accuracy depends on the window and step size. To overcome the accuracy limitations of the overlapping sliding window approach, we propose a hierarchical machine-learning framework that labels military movement patterns by combining change point detection, deep learning, and logic. The hierarchical model's performance was compared to a ConvLSTM model.

## Methods

Thirty-three members of the Canadian Armed Forces completed military transition tasks while donning a 17-sensor inertial measurement unit suit (MVN Link, Movella, US; [2]) to record whole-body movements at 240 Hz. The tasks were manually labelled into sub-movements (n = 29). Each task contained between eight and 25 sub-movements.

A ConvLSTM was trained using segment accelerations, angular velocities, positions, and joint angles in 3D from all sensors. The dataset was separated following a 70:15:15 training, validation, and testing split. The model, containing four convolutional and two LSTM layers, was trained using an optimal sliding window of 240 and a step of 48 frames. Results from the ConvLSTM were processed through a logical algorithm to ensure real-world constraint adherence.

A hierarchical machine learning framework was developed to automatically label sub-movements in a stepwise manner. Trials were first separated into static versus dynamic segments using a pruned exact linear time model. Static segments were classified as one of seven possible labels using a one-dimensional convolutional neural network, with label-specific adjustments implemented in the framework to correct start and end frames. Running segments were identified within the dynamic segments using the ConvLSTM model. A series of logical algorithms were then used to identify the dynamic transition sub-movements (n = 21) that connect the identified static or running segments (e.g., run-to-kneel, kneel-to-stand).

The performance of both techniques was evaluated using accuracy and F1 scores for each trial. Movement pattern sequences were compared to ground truth labels using the longest common subsequence method.

## Results and Discussion

The hierarchical model outperformed the ConvLSTM model in labelling accuracy, F1-score, and movement pattern sequence identification (Table 1). The hierarchical model's strong ability to identify the correct sequence of movement patterns within a trial indicates that the predicted labels are congruent with the true movement patterns and contain no additional or missing movements.

**Table 1:** Performance metrics for the hierarchical framework and the deep convolutional long-short-term memory neural network model.

| Approach | Accuracy (%) | F1-score (%) | Sequence (%) |
|---|---|---|---|
| Hierarchical | 90.28 ± 4.90 | 87.92 ± 5.34 | 95.90 ± 6.31 |
| ConvLSTM | 74.05 ± 9.16 | 71.48 ± 8.14 | 69.28 ± 13.6 |

## Conclusions

The proposed hierarchical framework can reduce the time burden of labelling movement patterns within military training exercises. Consequently, military stakeholders can quickly perform movement-specific analyses to accelerate knowledge advancements in military biomechanics. Work is ongoing to further improve the hierarchical framework.

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## References

[1] Mavor, MP et al. (2022). *Appl. Ergon.*, **104**:103809.
[2] Mavor, MP et al. (2020). *Sensors*, **20**:1-14.