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Gym Exercise Recognition Using Deep Convolutional and LSTM Neural Network Based on IMU Sensor Data

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***Abstract*—This study delves into the utilization of wearable devices equipped with inertial measurement units (IMUs) to gather data for human activity recognition. It explores the application of deep neural networks for automatically identifying gym workouts using IMU sensors. Our methodology involves developing a framework that integrates convolutional neural networks (CNNs) to extract features from raw sensor data, followed by using long short-term memory (LSTM) recurrent neural networks to classify sequences. IMU data from accelerometers and gyroscopes are collected from 10 individuals performing 30 standard gym routines. The CNN-LSTM pipeline is supervised on a comprehensive dataset comprising multiple sensors and subjects to distinguish between different workouts accurately. During the evaluation, the CNN-LSTM model achieved an accuracy of 93.81% in categorizing 30 workout categories based solely on accelerometer data. Through augmentation, this accuracy is further improved to 95.75%. This solution outperforms independently utilized CNN and LSTM models and traditional machine learning approaches. Detailed assessments offer valuable insights into the benefits of combining diverse sensor types and model architectures for robust exercise classification. This research raises a precise and dependable wearable system for identifying gym exercises using deep neural networks. The findings suggest promising avenues for future exploration in human activity recognition, mainly focusing on utilizing on-body sensors and deep learning to analyze more complex human movements.**

***Keywords*—gym exercise activity recognition, deep learning, wearable sensor, IMU, multimodal HAR**

I. Introduction

Utilizing wearable gadgets with inertial sensors like accelerometers and gyroscopes is increasingly prevalent in monitoring fitness levels and tracking physical activities [1], [2]. The copious influx of motion data captured by these sensors offers intriguing prospects for the automated recognition of human activities [3]. Notably, the advancement of intelligent wearable devices with the ability to independently identify and classify gym exercises would greatly benefit individuals ranging from recreational enthusiasts to elite athletes [4]. However, crafting dependable models for automatically identifying exercises from wearable sensor data remains challenging [5]–[7].

One of the main difficulties in exercise identification with inertial measurement units (IMUs) is extracting meaningful features from the raw multivariate time series data [8]–[10]. Conventional approaches for extracting features from handcrafted data, such as statistical measures, temporal domains, frequency domain transformations, and heuristic tactics, need extensive knowledge in the field and do not effectively use the interconnections present in complex multi-sensor data with many dimensions. Traditional machine learning methods that depend on manually designed characteristics have shown minimal success in classifying exercises using IMUs [11]–[13].

Advancements in deep learning have introduced robust techniques such as convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. These methods effectively address the constraints of previous approaches [14]–[18]. CNNs can automatically extract distinctive characteristics from unprocessed time-series data collected from several sensors [19]. On the other hand, LSTM networks can capture the temporal patterns essential for tasks involving the categorization of sequences [20].

This study focuses on developing a sophisticated neural network framework that combines CNN and LSTM models to accurately identify gym workouts using IMU data. The system is designed to automatically provide feedback on the type of exercise, the number of repetitions, and the performance quality for typical strength training and aerobic workouts. A series of experiments were conducted using a standardized human activity recognition (HAR) dataset, which collected data from accelerometers, gyroscopes, and magnetometers on wearable devices worn by individuals performing various gym activities. These experiments aimed to enhance training and assessment capabilities. Our trials unequivocally demonstrate that the proposed CNN-LSTM pipeline not only outperforms traditional methods but also surpasses other deep learning baseline methods in recognizing exercises based on sensor data.

Automated monitoring of gym activities offers the potential for safer, more quantifiable, and efficiently directed strength and cardiovascular sessions. This study explores the use of deep neural networks to improve the functionality of wearable devices in fitness applications. The findings contribute to analyzing and recognizing human activities using IMU-based technology, showcasing the effectiveness of new machine-learning methods in this field.

II. Related Works

The field of HAR using wearable sensors has made significant progress due to the widespread availability of devices equipped with IMUs [21]–[23]. A significant amount of research is dedicated to using IMU data from accelerometers, gyroscopes, and other sensors to automate activity analysis, monitor exercise, and assess skill levels [24]–[27].

Before training shallow classifiers such as SVM or KNN, earlier research heavily depended on human feature engineering to extract statistical, temporal, or frequency domain features from segmented sensor windows [11]. Nevertheless, the incapacity often constrained the performance to capture intricate motion signatures and correlations across multi-sensor streams with many dimensions. Recently, deep learning methods using CNN and RNN structures have shown substantial advancements by directly learning feature representations from unprocessed sensor data tuned for the specific job at hand [28], [29].

Although these works showcase the possibility of deep learning, they mainly concentrate on a limited number of challenges. The sensor modalities are mostly confined to accelerometers and do not use the potential advantages of including other inertial and physiological information. Our study aims to develop a robust system for accurately identifying various strength training and cardio workouts utilizing a combination of sensors and advanced machine learning techniques. We use a CNN-LSTM pipeline that integrates data from many wearable sensors to improve identification performance. The proposed technique combines convolutional feature extraction with recurrent sequence modeling and is taught end-to-end; it must be explored for problems involving IMU-based behavior assessment.

III. The Proposed Methodology

The sensor-based HAR workflow used in this study consists of five primary procedures: data gathering, data pre-processing, data segmentation, model creation, and model fine-tuning, as seen in Fig. 1.

A. Myogym Dataset

The research utilized a dataset named Myogym [30], obtained from 10 individuals participating in 30 unique gym exercises, each repeated ten times. An additional category labeled NULL signifies the absence of activity. Data collection involved sensors embedded in a Myo armband on the right forearm. This armband features a 9-axis IMU, including a 3-axis accelerometer and a 3-axis gyroscope, sampling data at 50 Hz. Moreover, it incorporates eight electromyographic (EMG) sensors to measure muscle activity in the arm. The Myogym dataset provides multi-modal time-series data, amalgamating information from inertial and EMG sensors to capture the dynamics of gym routines. The primary objective of this multi-sensor, multi-subject dataset is to aid in the development and evaluation of algorithms for detecting activities and fusing sensor data, enabling autonomous identification and classification of typical strength training and cardiovascular exercises. All details of the Myogym dataset can be summarized in Table I.

TABLE I
Summary of the Myogym dataset used in this study

Sensor Location	Wrist (Myo armband)
Sensor Modalities	3-axis Accelerometer 3-axis Gyroscope 8-channel eletromyography (EMG)
Sampling Rate	50 Hz
Number of Subjects	10
Number of Activities	31
Activity Classes	seated cable rows, single-arm dumbbell row, wide-grip pulldown behind the neck, bent-over barbell row, reverse grip bent-over row, wide-grip front pulldown, bench press, incline dumbbell flyes, incline dumbbell press and flyes, push-ups, leverage chest press, close-grip barbell bench press, bar skullcrusher, triceps pushdown, bench dip, overhead triceps extension, tricep dumbbell kickback, spider curl, dumbbell alternate bicep curl, incline hammer curl, concentration curl, cable curl, hammer curl, upright barbell row, side lateral raise, front dumbbell raise, seated dumbbell shoulder press, car drivers, lying rear delt raise, and the null category.

B. Data Pre-processing

During the initial data processing phase, the raw sensor data was manipulated to reduce noise and normalize it. To tackle signal noise, an average smoothing filter was employed in our study, covering all three axes of the accelerometer sensor. Following this, the sensor data was standardized to overcome model learning challenges, ensuring uniformity in the data range and facilitating faster convergence of gradient descents. Subsequently, the normalized data was segmented using fixed-width sliding windows of 2 seconds duration, with a 50% overlap.

C. The Proposed CNN-LSTM model

By effectively extracting and learning its inherent characteristics, CNNs demonstrate notable efficiency when handling one-dimensional sequence data, such as multivariate time series data. Additionally, there is a viable approach to employing a hybrid model, combining a CNN with an LSTM backend.

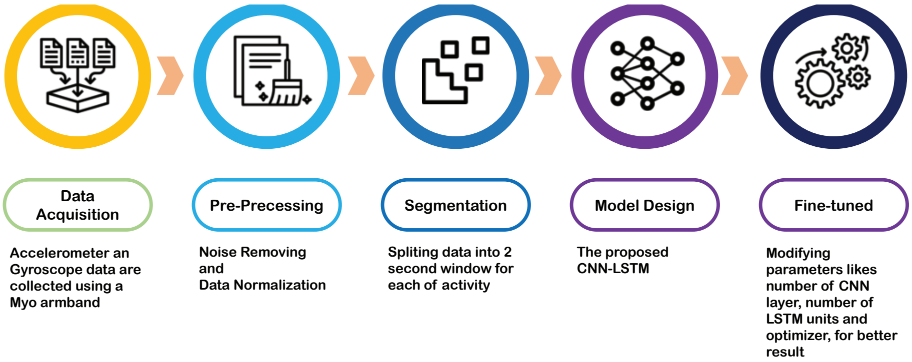

Fig. 1. The HAR workflow based on wearable sensors used in this work.

In this configuration, the CNN initially processes input sub-sequences, subsequently forwarding them sequentially to the LSTM for further analysis. This hybrid model, the CNN-LSTM model, employs CNN layers for feature extraction from input data, while the LSTM specializes in sequence prediction. Based on analyzing sub-sequences as distinct blocks, the CNN-LSTM model first identifies critical features within each block, which are then interpreted by the LSTM. The architectural layout of the CNN-LSTM model is illustrated in Fig. 2, with associated hyperparameters detailed in Table II.

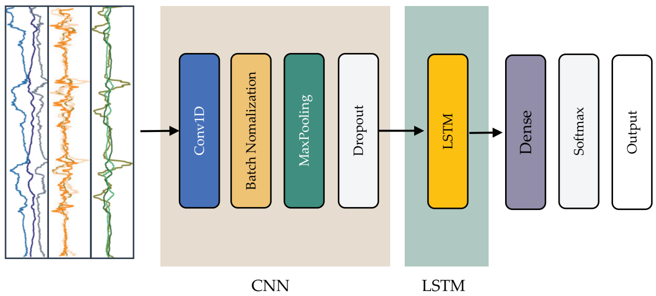

Fig. 2. The architecture of CNN-LSTM.

TABLE II
THE SUMMARY OF HYPERPARAMETERS FOR THE CNN-LSTM NETWORK PROPOSED IN THIS WORK

Stage	Hyperparameters		Values
Architecture	CNN Block		
	1D-Convolution	Kernel Size	5
		Stride	1
		Filters	256
	Batch Normalization		-
	Activation		ReLU
	Max Pooling		2
	Dropout		0.25
	LSTM Block		
	LSTM	Neural	128
	Dense		128
	Activation		SoftMax
Training	Loss Function		Cross-entropy
	Optimizer		Adam
	Batch Size		64
	Number of Epochs		200

IV. Experiments and Research Findings

To evaluate the suggested CNN-LSTM model's effectiveness in recognizing exercises, we conducted comparative tests. These tests compared the CNN-LSTM model's performance with that of deep learning baselines, which comprised solely CNN and LSTM models.

This study carried out all experiments on the Google Colab Pro+ platform, utilizing a Tesla V100 for computational processing. The Python programming language version and TensorFlow, Keras, Scikit-Learn, Numpy, and Pandas libraries were employed. NumPy libraries facilitated matrix operations for data manipulation. At the same time, Pandas handled CSV files, and Scikit-learn was employed to distribute samples evenly across training, testing, and validation datasets based on classes.

The study evaluates the effectiveness of the CNN-LSTM pipeline in identifying gym exercises using sensor data. The performance of this pipeline is then contrasted with that of CNN and LSTM deep learning models, which serve as benchmarks. Three distinct combinations of inertial sensors from the collected dataset are employed in the experiments:

1) Accelerometer data alone
2) Gyroscope data alone
3) Multi-modal fusion of accelerometer and gyroscope data

This facilitates an examination of the data richness and recognition potential provided by each sensor stream compared to their combined usage. Performance metrics, including classification accuracy, loss, and F1-score, are presented across three randomized test folds. Critical findings for deep learning models utilizing accelerometer, gyroscope, and combined accelerometer-gyroscope data are summarized in Tables III, IV, and V, respectively.

Table III presents findings on the performance evaluation of deep learning models utilizing solely accelerometer data. The CNN-LSTM model outperforms others, showcasing an accuracy of 93.81% and an F1-score of 82.87%. These results

TABLE III
PERFORMANCE METRICS OF DEEP LEARNING MODELS USING ONLY ACCELEROMETER DATA

Model	Recognition Performance (mean(±Std.))		
	Accuracy(%)	**Loss**	**F1-score(%)**
CNN	90.08%(±0.44%)	0.48(±0.03)	69.60%(±1.30%)
LSTM	92.54%(±0.15%)	0.29(±0.01)	78.58%(±0.69%)
CNN-LSTM	93.81%(±0.48%)	0.19(±0.01)	82.87%(±1.32%)

highlight the advantages of merging convolutional and recurrent neural networks for sensor-based exercise recognition instead of employing each method independently. The LSTM model achieves a higher accuracy rate of 92.54% than the CNN model's 90.08%.

However, the CNN exhibits a lower loss value of 0.48, contrasting with the LSTM's loss value 0.29. The transition from CNN to LSTM to CNN-LSTM illustrates the synergistic advantages of combining convolutional feature extractors with sequence modeling capabilities, further enhanced in the integrated model.

TABLE IV
PERFORMANCE METRICS OF DEEP LEARNING MODELS USING ONLY GYROSCOPE DATA

Model	Recognition Performance (mean(±Std.))		
	Accuracy(%)	**Loss**	**F1-score(%)**
CNN	82.62%(±0.33%)	0.89(±0.08)	41.36%(±0.69%)
LSTM	90.91%(±0.48%)	0.51(±0.02)	70.89%(±0.92%)
CNN-LSTM	93.95%(±0.30%)	0.23(±0.01)	81.51%(±0.43%)

The analysis of Table IV focuses on the performance evaluation of deep learning models utilizing solely gyroscope data. Once again, the CNN-LSTM model exhibits superior accuracy, minimal loss, and the highest F1-score, reaffirming its ability to utilize gyroscope sensor properties for effective, reliable workout detection. While the CNN and LSTM models achieve high accuracies of 82.62% and 90.91%, respectively, their deficient F1-scores indicate an imbalance between precision and recall, leading to misclassification of positive instances. Notably, the standalone CNN model experiences significant loss (0.89) and a low F1-score (41.36%) when processing gyroscope input, suggesting its limited capacity to handle inertial properties compared to LSTM and CNN-LSTM models, which excel in sequential modeling.

The integrated CNN-LSTM model overcomes the limitations of using CNN or LSTM separately for gyroscope data by combining automated feature extraction with temporal modeling, resulting in improved accuracy and recall, thus achieving a well-balanced and accurate classifier. Although the overall performance is inferior to that of accelerometer data, indicating differences in information richness, the CNN-LSTM consistently exhibits enhancements, suggesting that integrating various modalities would improve identification, a direction to be further explored in subsequent investigations.

The analysis of Table V revolves around evaluating deep learning models utilizing data from accelerometers and gyroscopes. The CNN-LSTM model, which merges information from accelerometer and gyroscope sensors, achieves the highest accuracy (95.75%), F1-score (87.71%), and lowest loss (0.16) among all methods.

TABLE V
PERFORMANCE METRICS OF DEEP LEARNING MODELS USING ACCELEROMETER AND GYROSCOPE DATA

Model	Recognition Performance (mean(±Std.))		
	Accuracy(%)	**Loss**	**F1-score(%)**
CNN	89.13%(±0.42%)	0.96(±0.10)	64.72%(±1.19%)
LSTM	94.29%(±0.15%)	0.30(±0.02)	82.92%(±0.73%)
CNN-LSTM	95.75%(±0.28%)	0.16(±0.01)	87.71%(±0.96%)

Combining multiple sensors enhances performance compared to using a single sensor, underscoring the complementary nature of accelerometer and gyroscope data. While both LSTM and CNN experience improvements through sensor fusion, the CNN-LSTM model demonstrates a more significant enhancement of 3-4%, underscoring the advantages of combining feature and temporal learning to differentiate between different exercises.

V. CONCLUSION AND FUTURE WORKS

In this study, we introduce a sophisticated neural network framework named CNN-LSTM. This framework combines CNN and LSTM models to accurately identify gym workouts using data collected from wearable IMU sensors. To assess the effectiveness of the CNN-LSTM model, we conducted experiments on the publicly available Myogym dataset, which contains accelerometer and gyroscope data. The comparative analysis reveals a significant improvement in accuracy, with the CNN-LSTM pipeline achieving an accuracy of 95.75%, compared to 89.13% and 94.29% for the standalone CNN and LSTM models, respectively. Integrating multiple sensor modalities demonstrates considerable efficacy, surpassing the performance of individual sensor-based approaches. This comprehensive investigation suggests that deep learning-based wearable applications could overcome the limitations of previous strategies, which relied on feature engineering for exercise recognition using sensor data.

This study underscores the potential for enabling widespread, accurate fitness monitoring without manual data collection. However, it is essential to note that our approach is tailored to 30 exercises in a controlled environment. Future research endeavors should explore customized models incorporating additional sensor modalities, such as heart rate while expanding the repertoire of exercises to enhance applicability in real-world scenarios.

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