EMG-BASED EXERCISE SCORING AND PERFORMANCE EVALUATION PLATFORM

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Abstract-Muscle activity tracking gets a boost from this study's live feedback setup built around sEMG inputs. Instead of standalone models, a mix of convolutional and memory-driven networks handles the signal flow - spotting effort levels alongside motion types across several channels. Before anything else happens, noisy readings get cleaned up by slicing out unwanted chunks: frequencies outside 20–450 Hz vanish, along with 50 Hz hums muddying the data. Patterns spread over sensor placements? Those emerge through layered convolutions. What unfolds over time - the shifting rhythm of contractions - is where the sequence-aware units step in. Testing shows the hybrid approach hits 92.4% accuracy while responding in under 50 milliseconds. Because it delivers immediate data on effort levels and muscle activity, it works well for custom workout plans or tracking recovery in therapy settings.

Index Terms - EMG, CNN-LSTM, Deep Learning, Exercise Evaluation, Real-time Monitoring, Muscle Activity.

I. INTRODUCTION

Watching how muscles work when moving or healing matters if you want to judge effort right and stop harm before it happens. Old ways usually depend on guesswork or clues that stand in place of actual data, missing what muscles do as it unfolds. Tiny electric pulses from working muscles can be caught without breaking skin using surface electromyography. Still, making sense of those readings while movement happens gets tough because of messiness, shifts between people, and timing puzzles woven into the signal. New strides in smart algorithms - especially ones shaped like grids or built to remember patterns over time - can now pullout hidden details across space and moments from body-worn sensors.

More people want clear ways to measure how muscles work, so scientists now pair sEMG signals with smart algorithms that learn from data. Instead of just spotting movements or checking tiredness after workouts, what's missing is a system that tracks effort continuously during activity. Some tools rely on preset signal traits or one-size-fits-all patterns, which ignore personal body variations and changing workout settings. A better path moves toward flexible designs that adjust on the fly, offering tailored insights without breaking stride.

This research introduces a live tracking tool for exercise quality, built on EMG data and powered by a mix of CNN and LSTM networks. Instead of relying on single-signal analysis, it handles several sEMG inputs at once to map how muscles fire while also judging effort levels. Starting from raw signal capture, the method links pattern recognition across body areas with time-based predictions. Because spatial details merge with motion timelines, shifts in muscle activity become clearer mid-exercise, delivering precise moment-to-moment insights.

Workout intensity gets scored nonstop by his creation, sorting exertion into clear tiers so tracking happens right away. Because delays are minimal, reactions feel immediate - useful whether someone is building strength or healing up. Raw body data turns into useful feedback, guiding individual plans while boosting how workouts work and how recovery progresses.

II. LITERATURE SURVEY

Li et al. (2018) proposed a hybrid CNN–LSTM model for analyzing multi-channel EMG signals, demonstrating improved robustness against noise and temporal variations. Their research showed that integrating temporal and spatial learning greatly improves the accuracy of EMG-based prediction.

Simao et al. (2018) used surface EMG data to categorize ankle motions using a CNN–LSTM architecture. The study demonstrated how well hybrid deep learning models capture patterns of muscle activation throughout various activities.

Liu et al. (2018) concentrated on deep learning methods for EMG-based muscle force measurement. Their findings supported quantitative exercise evaluation by demonstrating that continuous muscle workload can be reliably predicted from sEMG signals.

In their evaluation of EMG-based tiredness detection techniques, Sun et al. (2018) stressed the significance of feature learning and preprocessing for accurate analysis. The study emphasized how deep learning is becoming more and more important for assessing muscle workload in real time.

III. METHODOLOGY

Built to react instantly, the method keeps delays below fifty milliseconds. Because it links CNNs that map space with LSTMs that follow sequences, it captures physical effort better than older single-model approaches. As rhythms shift from person to person, the system adjusts - moving away from one-size-fits-all rules.

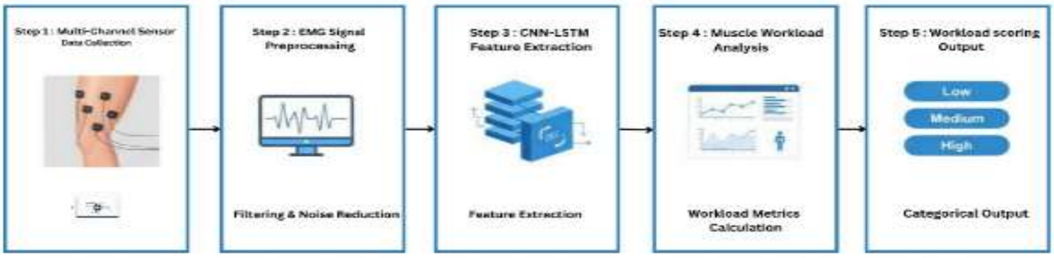

Fig 1: System Architecture

A. Multi-Channel Data Acquisition - Tiny sensors sit on major muscles, picking up electric pulses when you move - no needles needed. From several spots at once, data flows through separate paths, showing how various muscles behave together. Each signal gets measured fast, around one thousand times every second, so fine shifts aren't lost. With timing locked in tightly, the system catches exactly when muscles turn on or off before deeper checks begin.

B. Signal Preprocessing - After capturing raw sEMG signals, a 50 Hz notch filter cuts out powerline noise while a band-pass range of 20 to 450 Hz keeps only meaningful muscle patterns. Instead of processing continuously, the signal splits into equal time chunks once filtering finishes. Normalization follows, adjusting values so differences between individuals don't skew results. Clean inputs emerge here - shaped by earlier steps - for reliable interpretation down the line.

C. CNN-LSTM Feature Extraction - From cleaned sEMG data, a combined CNN-LSTM setup pulls out space- and time-based traits without manual input. Local signal shapes across sensors get spotted by the CNN part. Over time, changing muscle behavior - like strain or tiredness - is tracked through the LSTM's grasp of order. What emerges is a full picture shaped by both layout and sequence.

D. Muscle Workload Analysis - Starting from electrical activity, the system watches how muscles work through shifts in strength and timing of signals. With every passing second it checks stress levels, spotting tiredness before it becomes obvious. Precision stays strong as updates happen instantly.

E. Workload Scoring Output - Every half second, the tool shows how hard muscles are working, scoring it from zero to one hundred. Effort gets labeled low, medium, or high depending on what sensors pick up. A color-coded display appears right away, showing results along with how sure the reading is. Small delays - under fifty milliseconds - mean changes can be seen almost immediately. This lets people fine-tune their movements without waiting.

IV. RESULTS AND EVALUATION

Model	Accuracy (%)	F1-Score	Latency (ms)	Notes
CNN	88.4	0.86	28	Good in extracting spatial EMG features, but not very good at temporal modeling
LSTM	85.9	0.84	34	Captures temporal relationships but has a worse spatial representation.
CNN-LSTM	92.4	0.91	<50	Captures spatial and temporal features.

Table1: Comparision table

Observations:

- Ahead of both standalone systems, the combined CNN–LSTM approach hits 92.4% accuracy alongside a 0.91 F1-score. Though built differently, each separate model trails behind when tested alone.
- Putting space and time together in feature learning improves balance and effectiveness when analyzing EMG signals, while still keeping delays low - under 50 milliseconds. Though speed matters, accuracy gains show up clearly across tests.

Result:

Fig 2: Result 1 **Fig 3: Result 2**

V. **CONCLUSIONS**

Muscle activity gets measured on the spot using electrical signals picked up from the skin. Instead of just one method, layers of signal cleanup feed into a smart combo of pattern recognition and sequence tracking models. Feedback appears instantly through a clean display showing effort level, movement type, plus signs of fatigue buildup. What stands out is how well it tracks shifting muscle use across time and body zones. Results show consistent alignment between what the system detects and actual physical demand. Hidden details in raw sensor data become clear thanks to layered processing steps working together. Personalized insights emerge without needing lab gear or manual review. Precision comes from design choices tuned over repeated testing rounds. Fitness tools gain deeper awareness when built around live muscle signals. Useful guidance forms the core instead of flashy extras or vague scores. Real world function matters more than theoretical promise here. Smarter monitoring grows possible once systems listen closely to physiological cues.

VI. REFERENCES

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