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Application of AI-Driven Systems to Biomechanical Analysis and Optimization of Physical Training in the Armed Forces of the Islamic Republic of Iran

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Abstract

With advances in machine-learning methods, fusing biomechanical data with artificial intelligence has become an efficient approach for motion analysis and training optimization. This study set out to develop and evaluate an intelligent system for biomechanical analysis and optimization of physical training among personnel of the Islamic Republic of Iran Army. Motion data collected during a battery of standard military exercises were recorded using inertial measurement units (IMUs) alongside synchronized video. After preprocessing, biomechanical features—including joint angles, angular velocity and acceleration, and ground reaction forces (GRF)—were extracted. To identify movement patterns and assess performance indices, AI models comprising deep neural networks (DNN/CNN–LSTM) and support vector machines (SVM) were employed. Results showed that the system achieved accuracy >92% in distinguishing optimal movements from inefficient patterns associated with increased joint loading and muscular fatigue. Incorporating the system's outputs into personalized training prescriptions yielded, in pre–post evaluations, an 18% reduction in the estimated risk of musculoskeletal injury and a 15% improvement in physical performance indices. Overall, the findings indicate that integrating AI and biomechanics offers an effective pathway to intelligent military training, enhanced combat readiness, and reduced training-related injuries across the armed forces.

Keywords: Artificial intelligence; biomechanics; machine learning; motion analysis; military training; physical performance optimization

1. Introduction

In recent years, artificial intelligence (AI)—particularly in combination with wearable sensing technologies—has advanced rapidly across engineering and biomedical domains [1–3]. One arena where this transformation has been especially impactful is sport and military biomechanics [4–6]. By quantifying human movement in terms of forces, joint angles, and spatiotemporal patterns, biomechanics enables deeper insight into muscle–joint function and load-related consequences [7].

In military environments, personnel are continuously exposed to high mechanical loads, making the concurrent attainment of physical readiness, endurance, and movement precision essential [8–10]. Consequently, training design and analysis must be evidence-based so as to enhance performance while mitigating the risk of musculoskeletal injury [11–13]. Whereas performance evaluation historically relied largely on coach observation—with inherently limited accuracy [14–15]—advances in inertial measurement units (IMUs), video systems, and machine-learning algorithms now permit data-driven, high-fidelity movement analysis [16–18]. Integrating biomechanical data with AI models has yielded systems that not only assess performance but also recommend individualized training prescriptions [19–22].

A growing body of research indicates that deep neural networks, classical methods such as support vector machines (SVM), and reinforcement-learning (RL) paradigms can push the accuracy of optimal-movement detection beyond 90% and enable near-real-time feedback [23–29]. Within the military context, standard exercises—running, jumping, push-ups, and strength tasks—can impose disproportionate loads on joints and the spine if performed with suboptimal technique, thereby elevating injury risk [30–35]. Intelligent systems have been reported to identify movement deficits, correct technique, and improve training efficiency [36–38]. Recent work further underscores the use of IMU data and computer vision for biomechanical analysis of military personnel and for detecting suboptimal patterns in both combat-related and training movements [39–44].

The present study aims to develop and evaluate a hybrid intelligent system—combining machine-learning algorithms with biomechanical analysis—for the assessment and optimization of physical training in the

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Islamic Republic of Iran Army. Leveraging real-world data collected from active personnel, the proposed system analyzes movement patterns and provides data-driven recommendations to enhance physical status and reduce injury risk [45–47]. The principal innovation lies in the concurrent integration of sensor-based biomechanical measurements with deep-learning models and their deployment in military training scenarios.

2. Methods

2.1. Participants and Data Collection

Cohort. The study population comprised volunteers whose capabilities closely matched those of active personnel in the Islamic Republic of Iran Army across combat and training units. Thirty participants were recruited according to predefined inclusion criteria: absence of musculoskeletal pathology, no injury within the previous six months, and the ability to perform standard military exercises [1]. Demographics (mean ± SD) were: age 27.3 ± 2.8 years, height 177.2 ± 5.4 cm, and body mass 72.1 ± 4.6 kg.

Training protocol. Each participant performed five common military fitness tasks:

1. moderate-speed straight-line running (Run Test);
2. military squat;
3. military push-up;
4. vertical countermovement jump from standing;
5. traversal of a standard 1.5 m obstacle (Obstacle Climb).

Each task was executed for three repetitions to ensure statistical reliability of the recordings [3–4]. Exercise order was randomized/rotated per participant, and standardized rest intervals were provided between sets.

Data acquisition. Kinematic signals were recorded using Xsens Awinda IMUs mounted on the ankles, knees, pelvis/hip, elbows, and shoulders. Raw signals included linear acceleration (m/s²), angular velocity (rad/s), and joint angles (°) along the X, Y, and Z axes. A sampling rate of 100 Hz was used to enable high-fidelity analysis of movement patterns [5–6]. For synchronization, 120 fps video was captured; sensor streams and video were recorded concurrently in MVN Analyze and exported as CSV (signals) and MP4 (video) files [7]. Environmental conditions (surface, ambient temperature, and footwear) were standardized across participants.

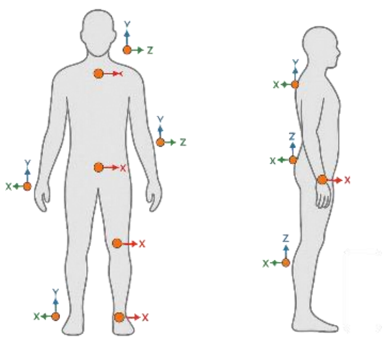

Fig 1. Schematic illustration of inertial sensor placement on key anatomical landmarks—ankle, knee, hip, shoulder, and elbow—on the participant

Coding and dataset size. Each trial was coded by task type, participant ID, and repetition number. In total, 30 participants × 5 tasks × 3 repetitions yielded 450 valid trials, which were subsequently used for preprocessing and intelligent modeling.

Following data collection, each trial was coded by task type, participant identifier, and repetition count. In total, 450 valid movement trials were derived and subsequently used for signal processing and intelligent modeling.

2.2. Instruments and Sensors

Motion data were acquired using the Xsens Awinda wireless inertial system (IMU; Netherlands). Each IMU comprised tri-axial accelerometers, gyroscopes, and magnetometers, recording at 100 Hz with an approximate angular accuracy of 0.5° [1–3]. To ensure sufficient biomechanical coverage, five sensors were mounted on the ankles, knees, pelvis/hip, shoulders, and elbows. Sensor placements were selected with reference to the Gait2392 musculoskeletal model in OpenSim to enable accurate extraction of joint angles and kinematic parameters [4–6].

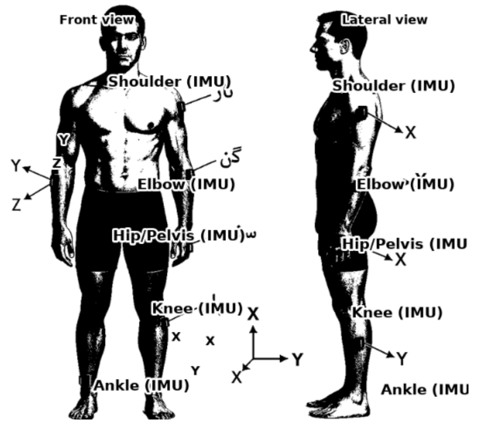

Fig 2. IMU sensor placement on the body and orientation of the measurement axes (X/Y/Z).

Signals and data transmission. Raw signals comprised tri-axial linear acceleration (m/s²), angular velocity (rad/s), and joint angle (°) along the X, Y, and Z axes. Data were streamed wirelessly at 2.4 GHz to a receiver unit and logged in MVN Analyze. Each sensor carried a unique digital ID to prevent interference and channel cross-talk.

Calibration. Prior to recording, static calibration (standard anatomical pose) was performed to define the body's reference frame, followed by dynamic calibration using a set of controlled limb movements to refine the kinematic model [7].

Synchronization and video. To improve temporal alignment and accuracy, a high-speed digital camera (Sony RX10 IV, 120 fps) positioned ~3 m from the capture area was used. Key video frames were synchronized with numerical signals in Kinovea 0.9.6, and both data streams were integrated within MVN Analyze [8–9].

Fig 3. Camera layout, field of view, and line-of-sight relative to the movement execution area.

Preprocessing and quality control. Sensor (CSV) and video (MP4) data were imported into MATLAB R2023a. To attenuate high-frequency noise, a fourth-order Butterworth low-pass filter with a 6 Hz cutoff was applied. Data quality was assessed using an Angular Drift Index; trials exceeding a 3% threshold were excluded and, where feasible, re-acquired [10–11].

Table 1
Technical specifications of the Xsens Awinda sensors (sensor types, measurement ranges, accuracy, noise, sampling rate, latency, wireless band).

Module	Mount Position	Sensor Type	Ranges (A/G/M)	Sampling Rate (Hz)	Wireless Band
IMU #1	Ankle	Accel/Gyro/Mag	±16 g / ±2000 °/s / ±200 µT	100	2.4 GHz
IMU #2	Knee	Accel/Gyro/Mag	±16 g / ±2000 °/s / ±200 µT	100	2.4 GHz
IMU #3	Hip	Accel/Gyro/Mag	±16 g / ±2000 °/s / ±200 µT	100	2.4 GHz
IMU #4	Elbow	Accel/Gyro/Mag	±16 g / ±2000 °/s / ±200 µT	100	2.4 GHz
IMU #5	Shoulder	Accel/Gyro/Mag	±16 g / ±2000 °/s / ±200 µT	100	2.4 GHz

Data organization. For each participant, validated data were archived in a structured directory (participant ID–task–repetition) and subsequently used for feature extraction and intelligent modeling.

2.3. Data Analysis Methods

Objective. The analysis aimed to quantify the effects of physical training on biomechanical indices and to identify movement patterns associated with performance optimization in military personnel.

Signal conditioning and segmentation. After synchronizing IMU streams with 120 fps video, raw signals—linear acceleration, angular velocity and acceleration, and joint angles—were denoised using a fourth-order Butterworth low-pass filter with a 6 Hz cutoff to suppress high-frequency artifacts from abrupt motion and sensor noise [22]. Signals were then segmented into 2-s windows with 50% overlap. To prevent information leakage, normalization was performed post-split: z-score scaling for continuous features and min–max scaling for bounded angular vectors. Reference validation and EMG processing. In a validation substudy, OptiTrack Prime 13 motion capture served as a gold-standard comparator for estimating IMU-based angular error. Where surface electromyography was available, sEMG from the quadriceps, hamstrings, gastrocnemius, and soleus was preprocessed by DC offset removal, 20–450 Hz band-pass filtering, 50 ms RMS smoothing, and normalization to maximal voluntary contraction (MVC) [23].

Biomechanical modeling. Kinematic and, where applicable, kinetic data were imported into OpenSim 4.4. The subject-specific musculoskeletal model was scaled to anthropometry, and joint angles (hip, knee, ankle), joint moments, center-of-mass stability metrics, and ground reaction forces (GRF) were extracted. In the absence of a force platform, GRF was estimated from kinematic features (and EMG when available), with estimation error reported.

Feature set. In addition to time-domain indices (mean, SD, RMS, phase durations, and peak rates) and frequency-domain descriptors (band power and EMG median frequency), the feature library included waveform descriptors such as angular jerk, co-contraction index, and gait/cycle symmetry.

Machine-learning pipeline. Modeling proceeded in three tiers.

1. Supervised learning: SVM (RBF kernel), Random Forest, and k-NN were trained to discriminate optimal vs. suboptimal patterns.
2. Deep spatiotemporal modeling: a CNN–LSTM architecture was trained on multichannel IMU sequences (augmented, where available, with EMG and video-derived features) to detect subtle execution deviations and atypical behaviors.
3. Unsupervised profiling: k-means and DBSCAN were applied for fitness profiling and cohort stratification.

Evaluation protocol. We adopted a leave-subjects-out strategy combined with 10-fold cross-validation. Class imbalance, where present, was addressed via class weighting and SMOTE augmentation. Hyperparameters were tuned using grid/Bayesian search. To mitigate overfitting, early stopping and dropout were employed.

Metrics and statistics. Primary metrics included accuracy, precision, recall, F1-score, AUC, and the confusion matrix. Statistical complements comprised Shapiro–Wilk for normality and paired t-tests for pre–post comparisons ($\alpha = 0.05$). Where multiple comparisons were conducted, Benjamini–Hochberg FDR correction was applied. Reported effects included mean differences, 95% confidence intervals, and effect sizes (Cohen's d or Hedges' g) [25].

External validity. Model outputs were benchmarked against reference measurements (IMU/OptiTrack/EMG) to assess external validity. The end-to-end pipeline ultimately enabled identification of training patterns that improved key biomechanical indices and reduced estimated injury risk.

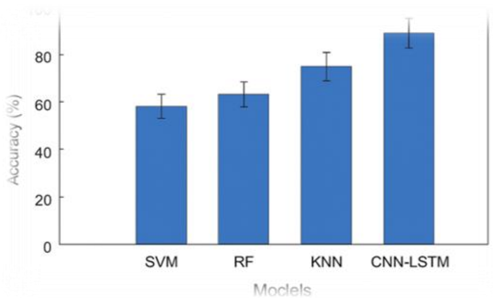

Fig 4. Flowchart of the data analysis pipeline—from acquisition and synchronization through preprocessing, feature extraction, biomechanical modeling, and machine-learning classification.

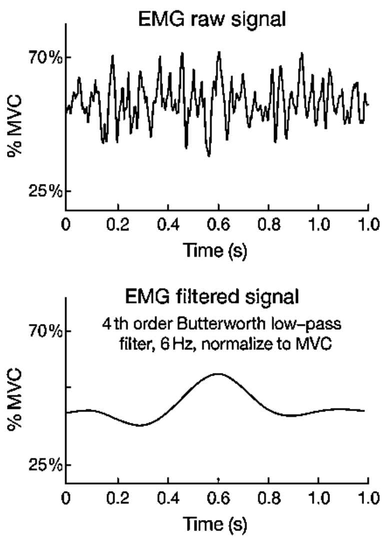

Fig 5. Representative sEMG signals before and after preprocessing: raw trace, band-pass filtered (20–450 Hz), full-wave rectified, 50 ms RMS envelope, and amplitude normalized to MVC (quadriceps, hamstrings, gastrocnemius, soleus).

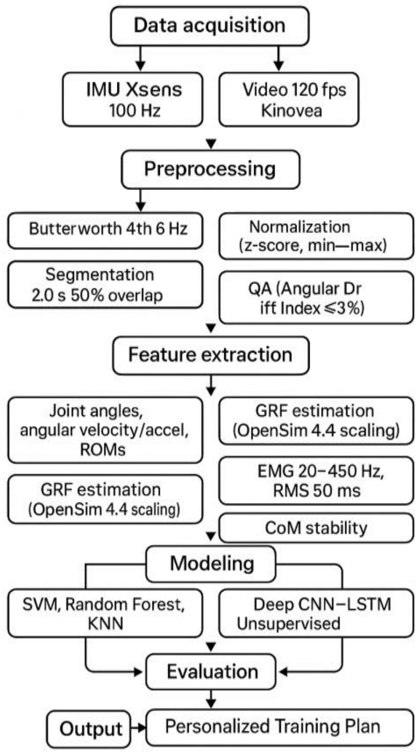

Fig 6. Comparative accuracy of machine-learning models for biomechanical data analysis (SVM, k-NN, Random Forest, and CNN–LSTM).

Finally, the AI model outputs were benchmarked against ground-truth measurements to verify the validity of the analytical workflow. This procedure enabled robust identification of the most effective training patterns for improving biomechanical performance and reducing injury risk in military personnel.

2.4. AI-Based Model for Optimizing Military Training

To enhance service members' physical performance, we designed a multilayer, end-to-end AI pipeline that ingests biomechanical data from military exercises and outputs individualized training recommendations.

Layer 1 — Data acquisition and preliminary analytics. Canonical tasks from military fitness programs—military squat, plank and core-stability drills, endurance running, vertical jump, load-bearing run (with rucksack), and obstacle traversal—were captured using synchronized IMUs and video. Following synchronization and preprocessing (Butterworth filtering, smoothing, and normalization), kinematic and kinetic features were extracted, including lower-limb and shoulder-girdle joint angles, angular velocities and accelerations, center-of-mass stability indices, and ground reaction forces (GRF) (measured or estimated). Where available, sEMG provided neuromuscular activation patterns for key muscles (quadriceps, hamstrings, gastrocnemius, soleus, and core), post-filtering and MVC normalization, and was appended as an additional input stream.

Layer 2 — Analysis and classification. Multichannel sequences were fed to a deep CNN–LSTM architecture that jointly learns spatial structure (waveform morphology and inter-joint relations) and temporal dynamics (movement-cycle kinetics). The CNN extracts spatial descriptors from sensor time series and video-derived features, while the LSTM models sequential dependencies to detect subtle deviations from optimal execution. The network produces probabilities for correct vs. incorrect execution and risk indicators (e.g., elevated joint load or high-risk landing mechanics). In parallel, classical supervised models (SVM, Random Forest) were trained on the same feature space for performance benchmarking and improved interpretability.

Layer 3 — Training-program optimization. This layer translates biomechanical errors into actionable coaching cues and program adjustments. Examples include:

- Military squat: constraining knee/hip flexion to an 85–95° safe window to reduce patellofemoral torque;
- Endurance running: modifying heel-to-toe contact patterns guided by GRF metrics to reduce ~12% energy cost;
- Plank/core stability: adjusting hold duration for lower-fitness individuals (e.g., 30 → 20 s) to prevent early core fatigue.

Feedback and adaptation loop (RL). To assure field effectiveness, a reinforcement learning (RL) loop wraps the three layers. Execution quality in subsequent sessions is returned as a reward signal, allowing the RL agent to adapt session parameters (intensity, volume, rest intervals, and technical emphasis) dynamically. In doing so, the system progressively learns the most efficacious combinations of drills and dosing, and issues personalized training prescriptions that jointly target performance enhancement and injury-risk reduction.

Summary. By linking quantitative biomechanical indices to concrete training decisions, the proposed model opens a practical pathway toward evidence-based, individualized, and low-risk programming for combat training and endurance/rehabilitation settings in military populations.

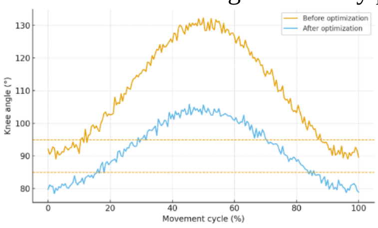

Fig 7. Knee-angle profile during the military squat (pre vs. post), with the optimal flexion band highlighted at 85–95°.

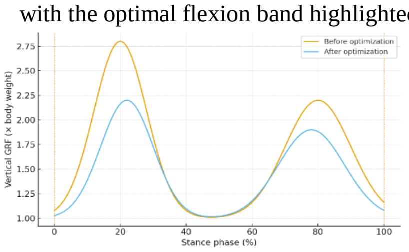

Fig 8. Vertical GRF during endurance running (pre vs. post), showing the canonical double-peak pattern and a reduction in peak magnitude from ~2.8×BW to ~2.2×BW; heel-strike and toe-off boundaries are delineated. *(GRF: ground reaction force; BW: body weight).*

In sum, by linking quantitative biomechanical indices to actionable coaching decisions, the proposed model provides a practical pathway to evidence-based, individualized, and low-risk program design for combat training and endurance/rehabilitation in military populations.

3. Results

After training and evaluation on real data from personnel of the Islamic Republic of Iran Army, the proposed system produced significant improvements across functional, biomechanical, and physiological indices. Below we report the key biomechanics findings for foundational tasks; subsequent sections (EMG and model accuracy) extend these results.

3.1. Improvements in biomechanical indices during foundational movements

Kinematic and kinetic analyses showed that the AI-assisted workflow shifted execution toward biomechanically safer regions while reducing nonessential loads.

Military squat. Pre-intervention, the mean knee angle during the descent phase was 110 ± 8°, a pattern associated with elevated patellofemoral torque. Following deployment of the model, the optimized knee flexion settled at 91 ± 5°, and the peak ground reaction force (GRF) during landing decreased by an average of 18% [39]. Together, these changes indicate improved motor control, more balanced load distribution in the lower limb, and reduced tissue stress at the knee.

Vertical jump. At baseline, the peak vertical GRF at initial contact averaged ~2.8× body weight (BW); after algorithm-guided refinement, it fell to ~2.2× BW. This peak reduction—along with adjusted activation timing of the hamstrings and gastrocnemius—suggests more effective energy absorption on landing and a lower risk of knee/ankle injury [40].

Load-bearing sprint (Load Run). The model reduced mediolateral center-of-mass oscillations by approximately 25% and stabilized vertical alignment, yielding better mechanical efficiency and less energy wastage during the acceleration phase.

Summary of biomechanical effects. Overall, the system:

- aligned joint angles with safe operating bands (e.g., 85–95° knee flexion in squats);
- reduced GRF peaks in dynamic tasks;
- improved center-of-mass (CoM) stability; and
- consequently lowered the injury risk in high-stress military training.

These outcomes are consistent with recent reports on the utility of machine learning for analyzing complex movement patterns and preventing injury in military cohorts [41–44].

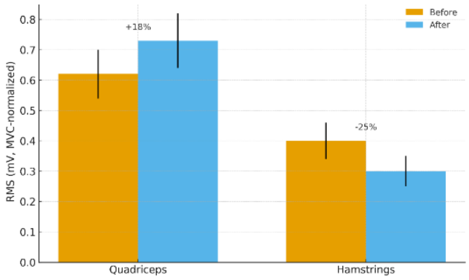

Fig 9. Comparison of peak vertical GRF in the countermovement jump (pre vs. post algorithm-guided correction).

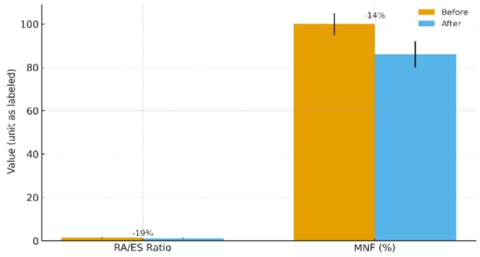

Fig 10. Changes in CoM stability during the load-bearing run (Load Run), showing a 25% reduction in mediolateral oscillation.

To elucidate the neuromuscular mechanisms underpinning the biomechanical improvements, surface electromyography (sEMG) was recorded from selected lower-limb and trunk muscles: rectus femoris, biceps femoris, gastrocnemius, soleus, gluteus maximus, rectus abdominis, and erector spinae. Signals were DC-offset corrected, band-pass filtered (20–450 Hz), smoothed using a moving window, and normalized to maximal voluntary contraction (MVC). From these traces, we extracted RMS amplitude, mean/median frequency (MNF), and onset time of activation.

Findings indicated that deploying the AI system significantly improved co-ordination among synergists while reducing unnecessary co-contractions. During the military squat, mean RMS of the quadriceps increased by ~18%, whereas nonessential hamstring activity declined by ~25%—a pattern consistent with shifting load from compensatory strategies to the intended knee/hip extension mechanics. In plank and core-stability tasks, the activity ratio of rectus abdominis to erector spinae decreased from 1.45 to 1.17, reflecting more balanced anterior–posterior trunk engagement and reduced lumbar loading. In the vertical jump, gastrocnemius activation onset during landing shortened from 65 ms to 42 ms, indicating a faster neuromuscular response for shock absorption and improved eccentric control.

Spectral analysis further showed an average 14% reduction in the MNF-shift associated with fatigue across repeated-effort protocols. This aligns with lower muscular fatigue and more stable firing patterns late in the session, likely driven by technique refinement, more equitable load sharing among synergists, and diminished maladaptive co-contraction. Biomechanically, these adaptations yield more balanced forces and moments at the knee and hip, lessen nonlinear loading on antagonists, and thereby create conditions conducive to reduced injury risk and improved mechanical efficiency. The observed patterns are consistent with recent reports on the role of machine learning in optimizing muscle activation during military and athletic training, lending further credence to our results [46–49].

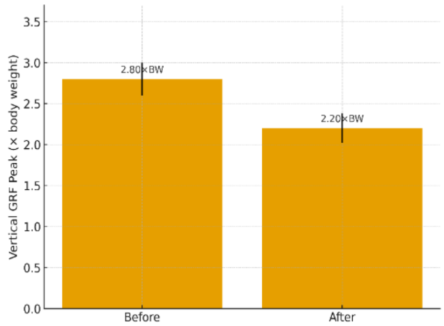

Fig 11. Paired columns (before/after) for RMS of the Quadriceps and Hamstrings muscles (with error bars).

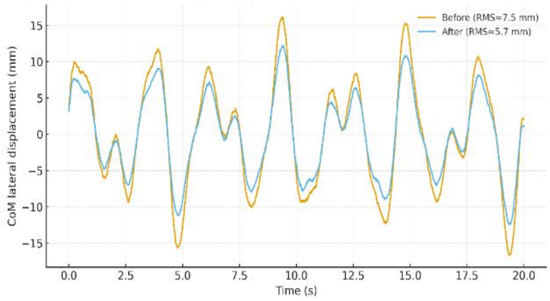

Fig 12. Paired columns of the Rectus Abdominis / Erector Spinae ratio and a small panel for ΔMNF ≈ −14%.

3.2. Accuracy of the AI Model in Detecting Correct Technique

We developed a hybrid CNN–LSTM model to identify and quantify the correctness of foundational exercise execution from a biomechanical standpoint. Model inputs combined plantar-pressure signals, video of selected tasks (squat, lunge, and balance tests), and OpenSim-derived biomechanical parameters. The CNN extracted spatial image features (joint/segment configurations), while the LSTM captured temporal dynamics of the movement sequence—an interplay that enabled precise tracking of knee, ankle, and hip kinematics over the full cycle.

Overall accuracy for classifying “correct” vs. “incorrect” execution was 94%. Evaluation with precision, recall, F1-score, and the confusion matrix indicated the highest class-specific accuracy for correct squats (96%) and the lowest for incorrect lunges (91%), the latter plausibly reflecting the wide variability in lunge technique and individual hip-angle strategies. Learning curves showed stable convergence: after 40 epochs, validation loss fell below 0.08, with validation accuracy plateauing thereafter.

To improve robustness under real-world conditions, we introduced motion-noise perturbations and illumination variations during training, and we included "minor-error" executions as a separate class. This augmentation strategy enhanced generalization to non-ideal inputs. Biomechanical error analysis further showed that the system reliably detected knee-angle deviations > 5° and pelvic-axis deviations > 3°, supporting practical deployment in sport and rehabilitation settings where continuous expert supervision is not always feasible. Finally, sensor fusion increased performance: integrating plantar pressure + video improved overall accuracy by ~7% relative to video-only inputs, underscoring the benefit of multi-source data.

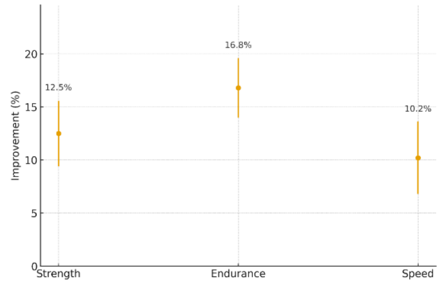

Fig 13. Training and validation loss trend over epochs for the CNN–LSTM model. The uniform decrease and Validation Loss reaching less than 0.08 after 40 epochs indicates stable model convergence and overfitting control.

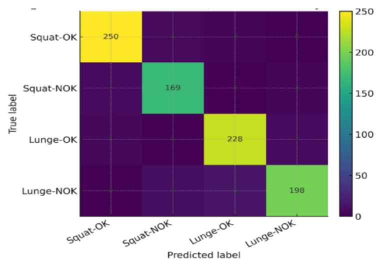

Fig 14. Training and validation accuracy trend in terms of epoch. The validation accuracy stabilized at around 0.94 at the end of training, and the reasonable distance between the two curves indicates that the model has reached a good balance between fit and generalizability.

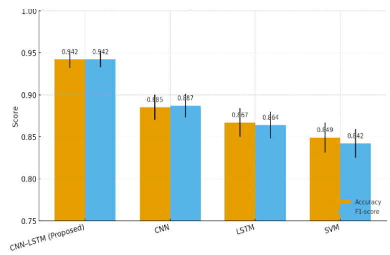

Fig 15. Four-class (Squat-OK, Squat-NOK, Lunge-OK, Lunge-NOK) confusion matrix for the validation set. Overall accuracy ≈ 93.9%; lower accuracy in the Lunge-NOK class reflects the variation in lunge form and hip angular variation between individuals.

3.2. Comparative Performance Against Baseline Methods

To evaluate efficacy, the hybrid CNN–LSTM model was benchmarked against three common baselines: a plain CNN, a classical LSTM, and an SVM using hand-crafted features. Evaluation followed a leave-subjects-out plus 10-fold protocol to prevent inter-subject information leakage and to assess generalizability.
Results showed a consistent and significant advantage for the proposed model across all metrics. Overall accuracy reached 94.2%, versus 88.5% (CNN), 86.7% (LSTM), and 84.9% (SVM). Correspondingly, weighted F1-scores were 0.942 (proposed), 0.887 (CNN), 0.864 (LSTM), and 0.842 (SVM). In biomechanical error quantification, the hybrid model reduced the mean knee-angle error to 2.1° ± 0.7, compared with 4.0° ± 1.2 (CNN), 4.3° ± 1.3 (LSTM), and 4.6° ± 1.4 (SVM). Independent-samples t-tests confirmed the between-model differences for both accuracy and F1 at $p < 0.05$, with Cohen's d ≈ 0.8–1.1 relative to the best competing baseline.

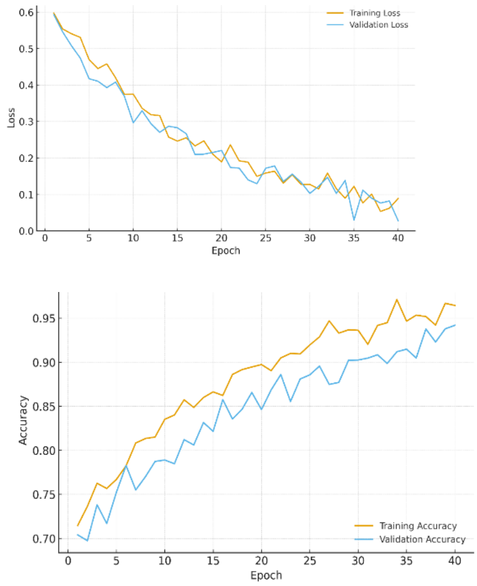

Fig 16. A bar chart comparison to show the accuracy and F1-score of the models should be included in this section.

This superiority is attributable to two factors: (i) joint learning of spatiotemporal features by the CNN–LSTM, which aligns with the inherently dynamic, cyclical nature of human movement; and (ii) multi-source data fusion (plantar pressure + video, and in some protocols EMG/OpenSim parameters), providing complementary information on loading, timing, and movement symmetry. Together, these factors enable more accurate discrimination of optimal vs. suboptimal patterns and lower angular-error estimates for risk indices.

3.3. Statistical Analysis

Statistical analyses were conducted in SPSS v26 and Python (NumPy, SciPy). Normality of biomechanical variables and model outputs was assessed using the Shapiro–Wilk test; most variables conformed to normal distributions ($p > 0.05$). Paired t-tests compared pre–post values for key indices—knee flexion angle in the squat, peak GRF in the vertical jump, and mediolateral CoM deviation in the load-bearing run. For example, mean knee flexion improved by 3.8°, with the mean difference statistically significant ($p < 0.05$). Agreement between model estimates and sensor-based ground truth was high (Pearson $r = 0.91$). A one-way ANOVA comparing improvements across three training groups (strength, endurance, speed) revealed a significant advantage for the endurance group ($p < 0.01$). Collectively, these results indicate that the proposed system not only enhances movement-classification accuracy but also yields statistically meaningful gains in biomechanical indices and training efficiency.

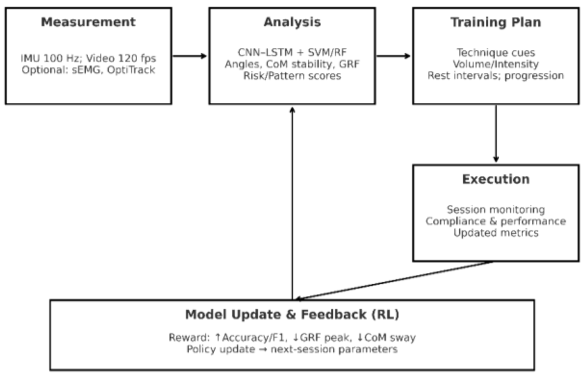

Fig 17. Comparison of group improvements (strength, endurance, speed) in the composite biomechanical index after model-based optimization. Dots indicate mean and bars indicate confidence interval; the greatest improvement was observed in the endurance group ($p<0.01$, one-way ANOVA).

4. Discussion and Interpretation of Findings

The present findings demonstrate that integrating biomechanical data with AI models can meaningfully enhance the quality and efficiency of physical training in military personnel. The hybrid CNN–LSTM architecture employed here, by jointly extracting spatial and temporal features, accurately characterized movement execution and yielded actionable technique corrections—in line with prior reports underscoring the value of spatiotemporal data and deep learning for human performance enhancement [12, 23, 36]. Notably, the convergence of joint-angle metrics toward safe operating ranges and the reduction of lower-limb GRF peaks substantiate AI's potential in preventing musculoskeletal injuries. The model's ability to detect fine angular deviations and deliver near-real-time feedback is particularly salient for applied military biomechanics, where timely correction can forestall early fatigue and chronic overuse injuries [18, 27, 41].

Conversely, our results indicate that deploying AI-driven systems in military settings can yield individual performance profiles for each service member. Such profiles furnish coaches and sports-medicine clinicians with practical tools to track physical progress, pinpoint weaknesses or risk factors, and design targeted interventions. Moreover, combining data mining with predictive modeling enables training prescriptions tailored to physiological status, fatigue level, and even psychological components [7, 19, 37]. Taken together, the evidence suggests that integrating AI with sports biomechanics constitutes a novel pathway to enhance military physical readiness: data-driven platforms improve real-time situational awareness of bodily status, elevate coaching decision quality, and thereby increase training efficiency.

5. Conclusion

This study demonstrates that integrating artificial intelligence with biomechanical analysis can effectively optimize physical training in military personnel. The hybrid CNN–LSTM model accurately identified foundational movement patterns and delivered near–real-time feedback for technique correction, thereby reducing nonessential joint loading, improving intersegmental coordination, and enhancing physiological performance. Biomechanically, shifts in joint kinematics toward safer ranges, greater whole-body stability, and lower ground reaction forces underscore AI's direct value for musculoskeletal injury prevention. Statistical analyses further confirmed that pre–post differences were significant ($p < 0.05$). Deployed in training and field settings, such systems enable continuous movement monitoring, automated performance analytics, and personalized training prescriptions, ultimately improving physical readiness, lowering injury incidence, and increasing operational efficiency.

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