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ADVANCED AI-BASED ATHLETE MONITORING AND INJURY PREVENTION IN SWITZERLAND: A MULTIMODAL DEEP LEARNING FRAMEWORK FOR PERSONALIZED PERFORMANCE OPTIMIZATION, REAL-TIME MUSCULOSKELETAL INJURY PREDICTION AND ANTERIOR CRUCIATE LIGAMENT INJURY PREVENTION

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Abstract

Rapid advances in artificial intelligence have created opportunities for data-driven athlete monitoring, performance enhancement, and proactive prevention of musculoskeletal and anterior cruciate ligament (ACL) injuries in Switzerland. A longitudinal dataset was compiled from 320 competitive athletes representing football, athletics, cycling, skiing, ice hockey, basketball, volleyball, and other endurance and indoor sports. The cohort included 198 male and 122 female athletes, with a mean age of 24.7 ± 4.3 years, body mass index of 22.9 ± 2.4 kg/m², and sporting experience of 7.2 ± 3.8 years. Multimodal information was collected through wearable inertial sensors, heart-rate monitors, GPS devices, training-load records, sleep and recovery assessments, biomechanical screening, medical histories, and athlete-reported wellness measures. After preprocessing, feature normalization, missing-value treatment, and class balancing, the data were divided into training, validation, and testing sets. The proposed architecture integrated convolutional neural networks, bidirectional long short-term memory layers, and an attention mechanism to capture spatial, temporal, and athlete-specific risk patterns. Its performance was compared with logistic regression, support vector machines, random forests, artificial neural networks, and XGBoost using accuracy, precision, recall, F1-score, and ROC-AUC. The multimodal model achieved 94.8% accuracy, 94.1% precision, 93.6% recall, a 93.8% F1-score, and a ROC-AUC of 0.972 for musculoskeletal injury prediction. For ACL-specific risk classification, it obtained 93.2% accuracy, 92.4% sensitivity, 94.0% specificity, and a ROC-AUC of 0.961, outperforming the strongest conventional

model, XGBoost, which achieved 92.6% accuracy and a 0.950 ROC-AUC. Explainable attention maps and continuously updated risk scores enabled coaches, clinicians, and athletes to identify workload spikes, asymmetric knee mechanics, neuromuscular fatigue, and insufficient recovery before injury occurrence promptly. The framework also facilitated transparent decisions and timely preventive interventions. Implementation of personalized recommendations increased the mean performance score from 78.4 to 90.0, improved recovery from 72.1 to 83.8, reduced excessive workload by 21.3%, overall injury risk by 27.6%, and high-fatigue sessions by 34.9%. Sleep duration increased from 6.9 to 7.4 hours, while training adherence rose from 82.7% to 91.3%. These findings demonstrate that multimodal deep learning can support proactive, individualized, and clinically informed athlete management within Switzerland's sports ecosystem.

INTRODUCTION:

Competitive sport increasingly depends on the continuous monitoring of athletes' physical workload, physiological condition, biomechanical movement, recovery status, and psychological well-being. Advances in artificial intelligence (AI), wearable sensing, and sports analytics have created new opportunities to transform these heterogeneous data into individualized recommendations for improving athletic performance and reducing injury risk. This transformation is particularly relevant to Switzerland, where football, skiing, cycling, ice hockey, athletics, basketball, volleyball, and endurance sports involve markedly different movement patterns, environmental conditions, training demands, and injury profiles. Despite the availability of sophisticated sports medicine services and monitoring technologies, integrating multimodal athlete data into timely and clinically meaningful decisions remains a substantial challenge. Musculoskeletal injuries are among the most important threats to athlete health, participation, and career development. Acute trauma and cumulative overuse can result in pain, reduced mobility, interrupted training, prolonged rehabilitation, and recurrent injury. These outcomes also impose considerable operational and financial burdens on athletes, clubs, healthcare providers, and sporting organizations [1]. Conventional injury-prevention practices generally rely on periodic physical assessments, retrospective medical records, isolated workload indicators, and subjective evaluations by coaches or athletes. Although these methods provide valuable information, they may not capture the complex and rapidly changing interactions among training intensity, fatigue, recovery, movement mechanics, previous injuries, and individual susceptibility. Consequently, early warning signs can remain undetected until performance deteriorates or an injury occurs. Anterior cruciate ligament (ACL) injury represents a particularly serious concern because it is frequently associated with surgical intervention, extended absence from sport, demanding rehabilitation, and an elevated risk of reinjury and long-term knee degeneration. ACL injury risk is influenced by multiple interrelated factors, including landing mechanics, knee valgus, lower-limb asymmetry, neuromuscular control, fatigue, training exposure, playing surface, sport type, previous injury, and anatomical characteristics. Female athletes may also demonstrate distinct risk patterns because of biomechanical, physiological, and hormonal factors [2]. Therefore, ACL prevention cannot be effectively supported by a single measurement or a uniform threshold applied across all athletes. A multidimensional and athlete-specific approach is required to recognize subtle risk patterns and facilitate preventive interventions before injury occurrence. Wearable inertial sensors, global positioning system devices, heart-rate monitors, biomechanical screening tools, sleep assessments, wellness questionnaires, and electronic medical records can collectively provide a comprehensive representation of athlete status. However, these sources generate data with different structures,

sampling frequencies, scales, and levels of reliability. Traditional statistical models often analyse individual variables independently or assume relatively simple relationships among predictors. Such assumptions may be inadequate for sports injury prediction, where risk emerges from nonlinear, time-dependent, and context-specific interactions. Moreover, relying on isolated indicators such as total training load, heart rate, or sleep duration can overlook the combined effect of multiple small changes occurring across physiological, biomechanical, behavioural, and environmental dimensions [3]. Deep-learning methods offer considerable potential for addressing these limitations. Convolutional neural networks (CNNs) can extract local and spatial patterns from sensor and biomechanical data, while bidirectional long short-term memory (BiLSTM) networks can capture dependencies across previous and subsequent points in sequential training records. Attention mechanisms can further identify the time intervals and features that contribute most strongly to an estimated injury risk. Their integration within a multimodal framework can support the joint analysis of movement characteristics, external workload, internal physiological responses, recovery indicators, and historical risk factors. This approach may improve predictive performance while generating dynamically updated athlete-specific risk estimates.

Nevertheless, the use of AI in athlete management presents several unresolved challenges. Many existing studies focus on a single sport, limited sensor modality, small cohort, or one injury category, reducing their applicability across diverse athletic populations. Other models emphasize predictive accuracy without showing how their outputs can be incorporated into daily coaching and clinical workflows. Black-box predictions may also limit trust when athletes and practitioners cannot understand why an individual has been categorized as high risk. In addition, variations in age, sex, sport, training history, competition schedule, and previous injury can produce substantial differences in risk. Models developed without appropriate personalization may therefore provide inaccurate or inequitable recommendations. Data privacy, informed consent, secure information handling, and responsible human oversight are equally important when sensitive health and performance information is processed. Within Switzerland, athlete monitoring must also account for the characteristics of its sporting ecosystem. Athletes frequently participate in indoor, field, endurance, winter, and high-altitude sports, creating diverse workload and environmental exposure patterns. Travel, seasonal changes, altitude, cold conditions, changing surfaces, and congested competition schedules may influence recovery and injury susceptibility [4]. A framework designed for this context should therefore accommodate multiple sports and data sources rather than depend on a fixed monitoring protocol. It should also support collaboration among athletes, coaches, physiotherapists, sports physicians, and performance analysts while preserving clinical judgment as the final basis for intervention. This study develops a multimodal deep-learning framework for personalized performance optimization, real-time musculoskeletal injury prediction, and ACL injury prevention among competitive athletes in Switzerland. Longitudinal data from 320 athletes across football, athletics, cycling, skiing, ice hockey, basketball, volleyball, and other endurance and indoor sports are integrated from wearable inertial sensors, heart-rate monitors, GPS devices, training records, sleep and recovery assessments, biomechanical screening, medical histories, and athlete-reported wellness measures. The proposed architecture combines CNN, BiLSTM, and attention components to learn spatial, temporal, and athlete-specific patterns. Its predictive performance is evaluated against logistic regression, support vector machines, random forests, artificial neural networks, and XGBoost using accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC. The principal contributions of this study are fourfold. First, it establishes a unified multimodal architecture that combines physiological, biomechanical, workload, recovery, behavioural, and clinical information. Second, it provides separate yet interconnected predictive functions

for overall musculoskeletal injury and ACL-specific risk classification [5]. Third, it incorporates explainable attention maps and continuously updated risk scores to improve the interpretability and practical usefulness of model outputs. Fourth, it translates predictions into personalized recommendations for workload adjustment, recovery management, movement correction, and preventive intervention. The effectiveness of the framework is assessed not only through classification metrics but also through changes in performance, workload exposure, recovery, fatigue, sleep duration, injury risk, and training adherence. By connecting continuous athlete monitoring with explainable prediction and human-guided intervention, this research contributes to the development of proactive sports medicine and individualized performance management. The proposed framework is intended to complement, rather than replace, coaches and healthcare professionals by converting complex multimodal information into timely and interpretable decision support. Its application may help reduce preventable injuries, enhance recovery, improve training quality, and support sustainable athletic performance across Switzerland's diverse sports environment.

Deep Learning for Spatial and Temporal Performance Patterns:

Athlete-monitoring data contain complex spatial and temporal patterns that cannot always be identified through conventional statistical approaches. Spatial patterns describe relationships among body segments, joint positions, landing mechanics, movement direction, pressure distribution, and lower-limb symmetry. Temporal patterns represent changes in workload, physiological response, fatigue, sleep, recovery, and movement quality across consecutive training sessions. Effective athlete monitoring therefore requires models capable of learning how these variables interact over both space and time. Convolutional neural networks (CNNs) are widely used to extract local and spatial features from wearable-sensor signals and biomechanical measurements. Convolutional filters can identify distinctive patterns associated with unstable landing, excessive impact, irregular acceleration, poor postural control, and abnormal joint movement. CNNs can also reduce dependence on manually engineered features by learning relevant representations directly from multidimensional data. However, a standalone CNN may not fully capture how workload, recovery, and injury risk develop across extended monitoring periods. Long short-term memory (LSTM) networks address this limitation by maintaining information across sequential observations. They can model the cumulative effects of training exposure, repeated fatigue, insufficient recovery, and changes in physiological readiness. Bidirectional long short-term memory (BiLSTM) networks further improve sequential analysis by examining temporal relationships in both directions during model training [6]. This allows each monitoring observation to be interpreted within its broader temporal context. Attention mechanisms strengthen these models by assigning greater importance to the features and time intervals most strongly associated with a predicted outcome. For example, the model may emphasize a sudden increase in training load, persistent sleep reduction, declining recovery, or deteriorating knee mechanics. As summarized in Table 1, CNN, BiLSTM, and attention components provide complementary functions in athlete monitoring and injury-risk analysis.

Table 1: Roles of deep-learning components in spatial and temporal athlete-performance analysis

Deep-learning component	Primary function	Athlete-monitoring application
CNN	Local and spatial feature extraction	Movement mechanics, impact patterns, joint behaviour, and sensor signals
LSTM	Sequential dependency learning	Workload progression, fatigue accumulation, sleep, and recovery

BiLSTM	Bidirectional temporal analysis	Interpretation of complete monitoring sequences
Attention mechanism	Feature and time-step prioritization	Identification of influential risk indicators
Multimodal fusion layer	Integration of learned representations	Combination of wearable, biomechanical, physiological, and clinical data
Fully connected output layer	Risk and performance classification	Musculoskeletal injury and ACL-risk prediction

Hybrid CNN–BiLSTM architectures combine spatial feature extraction with temporal pattern recognition. In this structure, CNN layers first detect local movement and physiological patterns, while BiLSTM layers examine how these patterns evolve across time. The attention mechanism then assigns greater weight to the most informative features and monitoring periods before the multimodal fusion and prediction stages. The relationship among these components is presented in Figure 1.

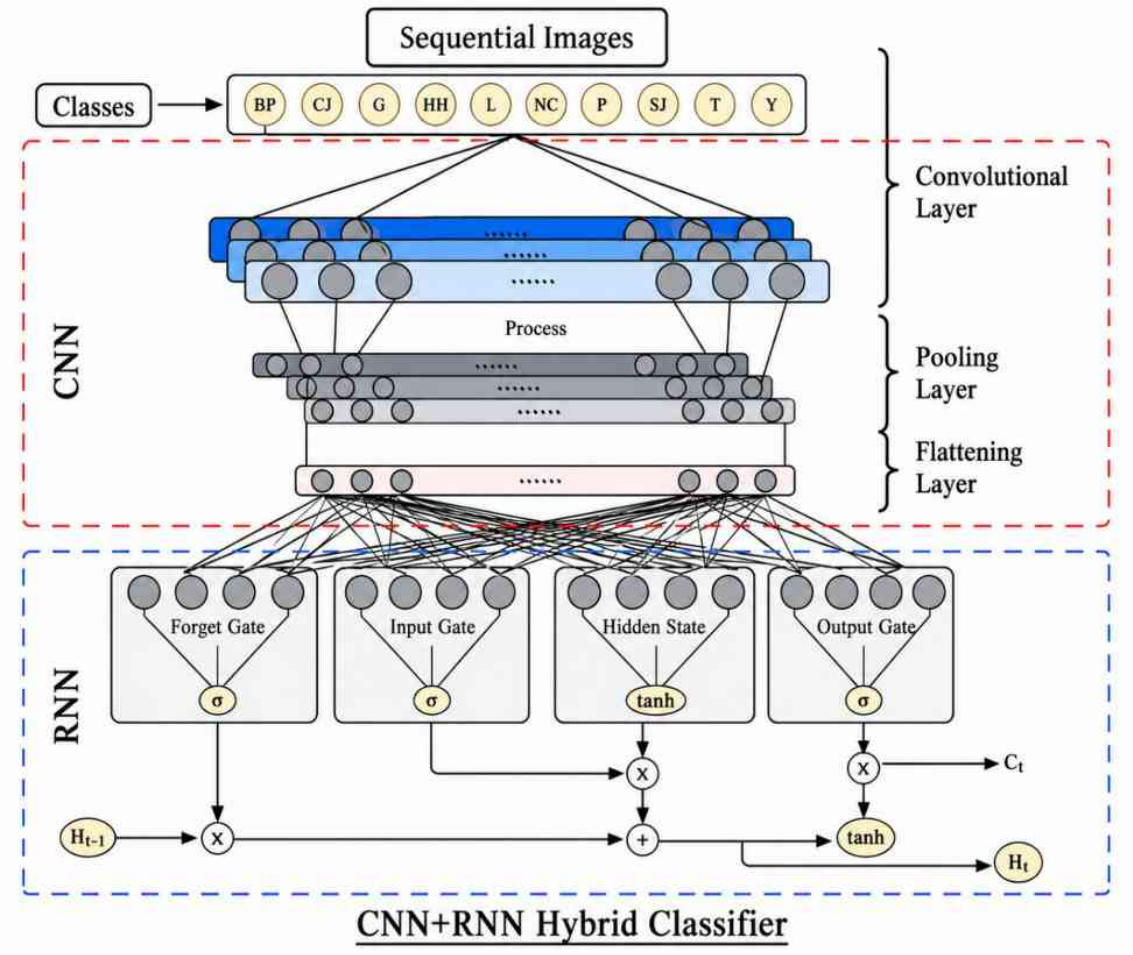


Figure 1: CNN–RNN hybrid architecture for sequential image classification.

The combined architecture is particularly appropriate for sports injury prediction because injuries generally result from interacting factors rather than a single abnormal observation. A sudden workload increase may become more important when accompanied by insufficient

sleep, neuromuscular fatigue, and altered landing mechanics. By jointly analysing these spatial and temporal relationships, the hybrid model can generate more individualized risk estimates and performance recommendations. Despite these advantages, deep-learning models require sufficiently large and representative datasets, consistent sensor measurements, robust preprocessing, and careful validation. They can also be difficult to interpret if explanatory mechanisms are not included. Accordingly, attention-based visualization and feature-importance analysis should accompany predictive outputs so coaches and clinicians can understand the major factors contributing to each risk estimate.

Real-Time Risk Scores and Human-in-the-Loop Decisions:

Real-time athlete monitoring requires more than accurate offline injury classification. A practically useful system must continuously process new physiological, biomechanical, workload, recovery, and wellness data and translate them into timely risk estimates. Dynamic risk scores allow coaches and clinicians to recognize changes in athlete readiness, identify early warning signs, and intervene before performance deterioration or injury occurs. Risk scores can be updated after each training session or whenever new sensor and wellness information becomes available. Instead of applying a fixed threshold to every participant, the system compares current measurements with the athlete's personal baseline, previous injury history, sport-specific demands, and recent training exposure [7]. This individualized approach helps distinguish between normal variation and clinically relevant changes. As shown in Table 2, predicted probabilities can be organized into low-, moderate-, and high-risk categories. Each category is accompanied by its principal contributing factors and an appropriate human-reviewed response. The thresholds should be optimized using validation data and subsequently examined by sports medicine professionals.

Table 2: Dynamic risk categories and recommended human-reviewed responses

Risk category	Illustrative probability	Suggested system response	Human decision
Low risk	<30%	Continue routine monitoring	Coach maintains the planned training program
Moderate risk	30–69%	Generate an early-warning notification	Coach or physiotherapist reviews training and recovery
High risk	≥70%	Issue a priority alert and recommend intervention	Clinical assessment and immediate training modification
Critical clinical concern	High risk combined with symptoms	Suspend automated recommendations and escalate the case	Sports physician determines participation or treatment

The risk score should not be interpreted as a diagnosis or certainty that an injury will occur. Instead, it represents the estimated probability of injury based on the athlete's current and historical data. Two athletes with similar probabilities may require different responses. For example, a high score driven primarily by insufficient recovery may require temporary workload reduction and improved sleep, whereas a score associated with knee valgus and lower-limb asymmetry may require biomechanical assessment and neuromuscular training. Human-in-the-loop decision-making is therefore essential. Coaches provide information about training objectives and competition requirements, physiotherapists assess movement quality and rehabilitation status, and sports physicians evaluate clinical symptoms and medical risk. Athletes also contribute important subjective information, including pain, fatigue, stress, and confidence [8]. Combining these

perspectives with AI-generated evidence can improve the relevance and safety of preventive decisions. The complete decision process is illustrated in Figure 2. New athlete data are processed by the predictive model, converted into dynamic risk scores, and explained through attention maps or feature-importance information. Coaches and clinicians then review the alert before selecting an intervention. Subsequent athlete responses are returned to the monitoring system, creating a continuous feedback cycle.

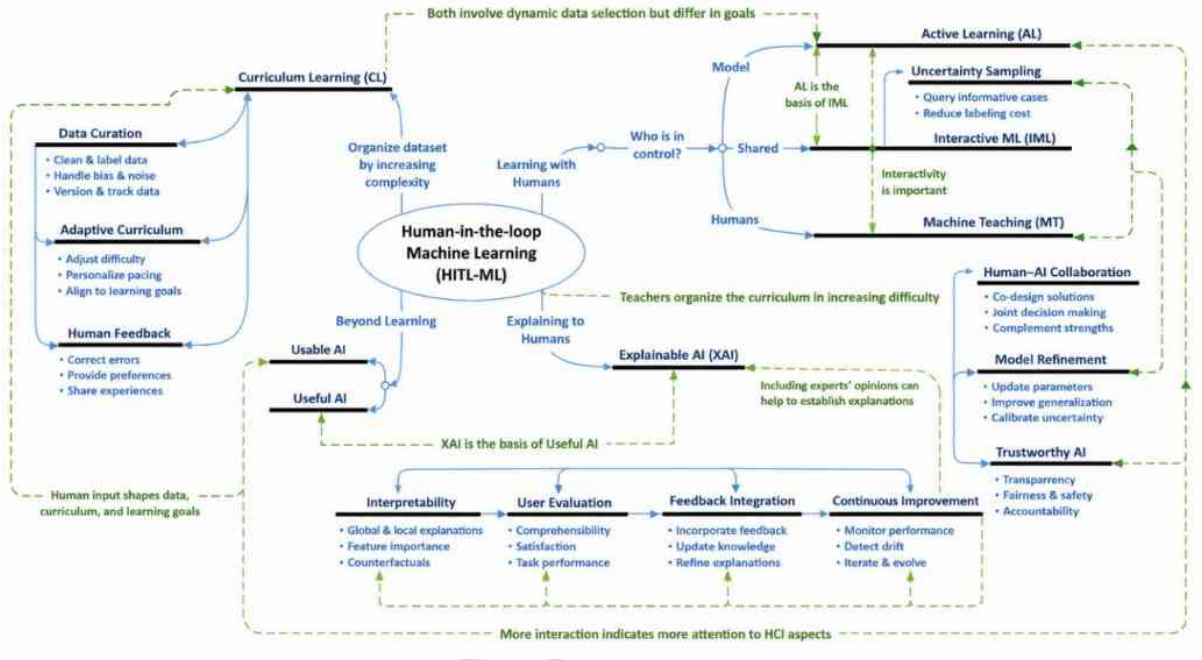


Figure 2: Real-time risk assessment and human-in-the-loop decision pathway.

Explainability strengthens this process by showing why a risk score has changed. Attention maps and feature-importance profiles may identify workload spikes, reduced sleep, neuromuscular fatigue, altered heart-rate recovery, or asymmetric knee mechanics as the main contributors. This information enables practitioners to select interventions that address the athlete's specific risk profile. A human-in-the-loop framework also reduces the likelihood of unnecessary training restrictions resulting from sensor errors or false-positive predictions. Professionals can consider contextual information that may not be available to the model, such as illness, equipment malfunction, unusual travel, tactical demands, or recent clinical findings. Consequently, real-time AI should function as an intelligent decision-support system rather than an autonomous authority over athlete participation and treatment.

Methodology:

This study employed a longitudinal, multimodal research design to develop and evaluate an artificial intelligence–based framework for personalized athlete monitoring, performance optimization, real-time musculoskeletal injury prediction, and anterior cruciate ligament (ACL) injury prevention. The research integrated physiological, biomechanical, workload, recovery, medical, and athlete-reported information collected during regular training and competition periods. This approach enabled the analysis of both immediate fluctuations and longer-term patterns in workload tolerance, physical readiness, neuromuscular fatigue, movement mechanics, and injury susceptibility. The overall research process included athlete recruitment, baseline assessment, continuous data acquisition, preprocessing, multimodal feature integration, deep-learning model development, comparative evaluation, risk

interpretation, and personalized intervention. Multimodal data were obtained from wearable inertial sensors, heart-rate monitors, GPS devices, training-load records, sleep and recovery assessments, biomechanical screening, medical histories, and athlete-reported wellness measures. Raw data were screened for duplicated records, missing observations, sensor interruptions, measurement noise, inconsistent timestamps, and physiologically implausible values. After quality control, continuous variables were normalized, categorical variables were encoded, and records collected at different sampling frequencies were synchronized into consistent monitoring intervals [9]. Feature engineering was performed to derive indicators of workload progression, cardiovascular response, movement asymmetry, knee mechanics, fatigue, sleep quality, recovery status, previous injury, and athlete-specific deviations from established baselines. The proposed architecture integrated convolutional neural networks, bidirectional long short-term memory layers, an attention mechanism, and multimodal feature fusion. CNN layers extracted local and spatial patterns from sensor and biomechanical data, whereas BiLSTM layers captured temporal dependencies across training, fatigue, sleep, and recovery sequences. The attention mechanism prioritized the features and monitoring periods contributing most strongly to injury-risk estimates. Model performance was compared with logistic regression, support vector machine, random forest, artificial neural network, and XGBoost using accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC. Explainable risk scores were subsequently reviewed by coaches, physiotherapists, and sports physicians before personalized training, recovery, or injury-prevention recommendations were implemented.

4.1-Athlete Cohort and Multisport Representation:

The study included 320 competitive athletes recruited from organized sports clubs, performance programs, and training environments across Switzerland. A stratified sampling strategy was employed to obtain meaningful representation across sex, sport category, competitive level, physical demands, training exposure, and injury history. The multisport design was selected because injury mechanisms, workload profiles, recovery requirements, and biomechanical demands differ considerably among field, court, endurance, winter, ice, and indoor sports. Including athletes from several disciplines allowed the proposed framework to learn generalizable risk patterns while preserving athlete- and sport-specific characteristics [10]. The cohort comprised 198 male and 122 female athletes, corresponding to 61.9% and 38.1% of the total sample, respectively. Participants had a mean age of 24.7 ± 4.3 years, a mean body mass index of 22.9 ± 2.4 kg/m², and an average sporting experience of 7.2 ± 3.8 years. Approximately 35% of participants were involved in team-based field sports, while the remaining athletes represented endurance, winter, ice, court, and other indoor disciplines. The principal demographic and sporting characteristics of the study population are summarized in Table 3.

Table 3: Demographic, sporting, and monitoring characteristics of the athlete cohort

Characteristic	Category or measure	Study information
Total sample	Competitive athletes	320
Sex distribution	Male	198 (61.9%)
	Female	122 (38.1%)
Age	Mean ± SD	24.7 ± 4.3 years
Body mass index	Mean ± SD	22.9 ± 2.4 kg/m²
Sporting experience	Mean ± SD	7.2 ± 3.8 years
Team-based field sports	Approximate representation	35%
Physiological information	Internal load	Heart rate, fatigue, recovery, and wellness

Primary analytical outcomes	Prediction targets	Musculoskeletal injury and ACL-specific risk

The participating athletes represented football, athletics, cycling, skiing, ice hockey, basketball, volleyball, and additional endurance and indoor sports. This distribution was particularly important for the intended application of the framework within Switzerland, where sporting activities range from high-intensity team competition to endurance and winter disciplines. The cohort therefore reflected diverse combinations of movement intensity, environmental exposure, surface conditions, contact demands, training frequency, and recovery requirements. Football athletes were exposed to repeated accelerations, decelerations, sprinting, cutting, physical contact, and rapid changes of direction. These movement demands can increase stress on the lower limbs and contribute to muscle, ligament, and joint injuries. Basketball and volleyball athletes performed frequent jumping, landing, pivoting, and lateral movements, making landing mechanics, knee alignment, and neuromuscular control particularly relevant [11]. Ice hockey involved high-speed skating, physical contact, rapid directional changes, and repetitive lower-limb loading, whereas skiing required balance, lower-limb stability, postural control, and adaptation to changing terrain and environmental conditions. Athletics and cycling introduced different performance and injury patterns. Depending on the event, athletics can involve sprinting, repetitive endurance activity, jumping, or throwing, with corresponding differences in workload and musculoskeletal stress. Cycling primarily involves repetitive lower-limb movement and sustained physiological loading, making cumulative workload, joint positioning, recovery, and overuse indicators especially important. The inclusion of these diverse disciplines enabled the model to examine whether similar physiological or biomechanical warning signals carried different meanings across sporting contexts. The structure of the cohort and its integration into the analytical framework are illustrated in Figure 3. Demographic, sporting, clinical, workload, physiological, biomechanical, recovery, and wellness information was collected for each athlete. These data were combined to establish individualized monitoring profiles and support both general musculoskeletal injury prediction and ACL-specific risk classification.

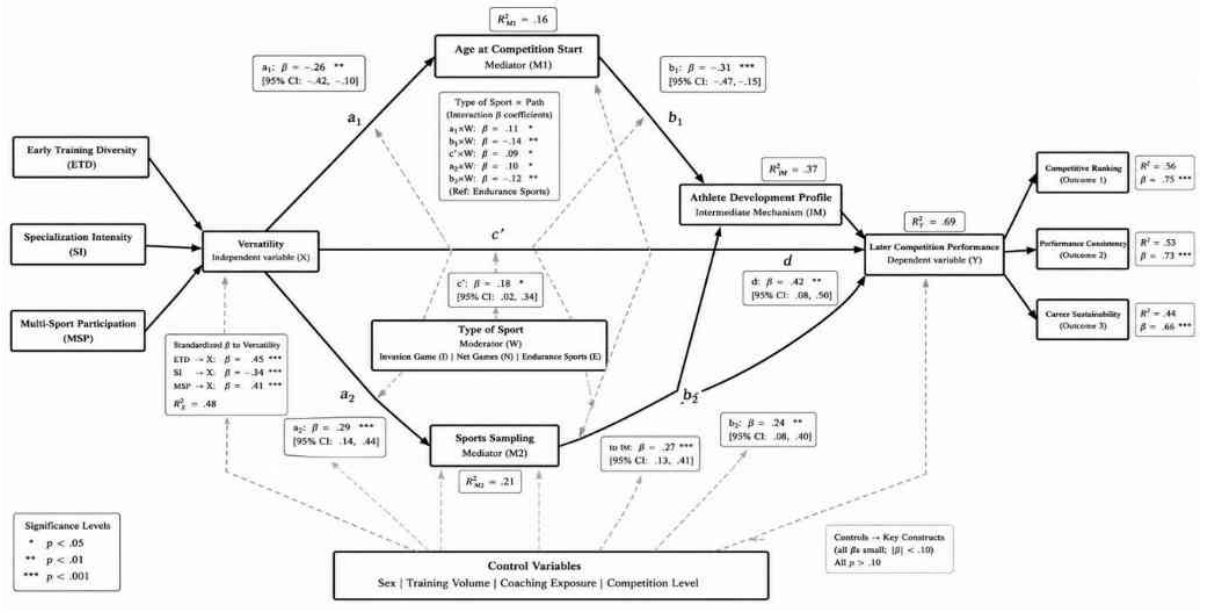


Figure 3: Moderated mediation model linking athletic versatility to long-term competitive performance outcomes.

Participants were eligible for inclusion if they were actively involved in structured competitive sport, regularly attended training, and were physically capable of completing the required baseline assessments. They were also required to provide sufficient longitudinal monitoring data and follow the designated procedures for wearable-sensor use, workload recording, sleep assessment, and wellness reporting. These requirements ensured that the model received sufficiently complete information to examine changes in athlete condition over time. Athletes were excluded when baseline assessments were incomplete, monitoring records were insufficient, wearable-device use was inconsistent, or major sensor-data deficiencies prevented reliable analysis. Athletes with medical conditions that prevented regular participation during the monitoring period were also excluded from the final predictive dataset when adequate longitudinal information could not be obtained. Temporary illness or minor interruption did not automatically result in exclusion; instead, the associated observations were documented and examined during data-quality assessment [12]. Baseline demographic information included age, sex, height, body mass, and body mass index. Sporting characteristics included primary discipline, playing position where applicable, competitive level, weekly training exposure, competition frequency, and total sporting experience. These variables were included because athletes with different competitive backgrounds may demonstrate distinct workload capacities, recovery patterns, and injury susceptibilities. Clinical profiling included previous musculoskeletal injury, ACL history, surgical history, rehabilitation status, injury recurrence, affected body region, and time lost from training or competition. Previous injury was treated as an important contextual variable because incomplete rehabilitation, residual weakness, altered movement patterns, or psychological concerns may influence future injury risk. However, historical injury information was not used independently; it was evaluated alongside current workload, recovery, physiological, and biomechanical measurements. Baseline biomechanical screening assessed movement characteristics relevant to general lower-limb and ACL risk. Jump-landing tasks, single-leg movements, balance tests, and sport-specific directional changes were used to evaluate knee control, trunk positioning, impact management, postural stability, and lower-limb symmetry. The biomechanical profile provided a reference against which subsequent changes in movement quality could be assessed. This was particularly useful for identifying athlete-specific deviations that might not exceed general population thresholds.

4.2- Multimodal Athlete Data Acquisition:

Multimodal data were collected to develop a comprehensive representation of each athlete's physical workload, physiological response, movement mechanics, recovery condition, wellness status, and previous injury profile. Data acquisition was conducted during regular training sessions, competitive events, and scheduled biomechanical assessments. Combining these sources enabled the framework to evaluate how external training demands interacted with internal responses and athlete-specific risk factors. Wearable inertial measurement units containing accelerometers and gyroscopes were used to capture body acceleration, rotational movement, impact magnitude, movement stability, and left–right asymmetry. GPS devices recorded external-load indicators, including total distance, high-speed running, sprint exposure, acceleration, deceleration, movement intensity, and positional demands. Heart-rate monitors provided internal-load information through average heart rate, peak heart rate, time spent within intensity zones, cardiovascular strain, and post-exercise recovery [13]. Training records supplied contextual information about session duration, activity type, perceived intensity, resistance-training volume, match exposure, competition frequency, and recovery periods. Sleep duration, sleep quality, fatigue, muscle soreness, stress, perceived recovery, and general readiness were collected using digital monitoring devices and structured athlete-reported assessments. Biomechanical screening contributed information about knee alignment, landing impact, joint control, balance, trunk movement, hip–knee coordination, and lower-

limb symmetry. Clinical data included previous musculoskeletal injuries, ACL history, surgical procedures, rehabilitation status, injury recurrence, affected body region, injury severity, and time lost from training or competition. These historical variables were necessary because previous injury and incomplete rehabilitation can influence movement behaviour, workload tolerance, and future injury susceptibility. The principal data sources and extracted variables are summarized in Table 4.

Table 4: Multimodal athlete data sources and extracted monitoring variables

Data modality	Acquisition source	Principal variables
Inertial movement data	Accelerometers and gyroscopes	Acceleration, rotation, impact, stability, and asymmetry
External workload	GPS and tracking devices	Distance, speed, sprint exposure, acceleration, deceleration, and positional movement
Physiological response	Heart-rate monitors	Average heart rate, peak heart rate, intensity zones, cardiovascular load, and recovery
Training exposure	Digital training records	Session duration, exercise type, match exposure, resistance volume, and competition frequency
Environmental context	Training and competition records	Surface, setting, altitude, weather, and travel where available

Data from different sources were collected at varying frequencies. Wearable and GPS devices generated high-frequency measurements during physical activity, whereas sleep, wellness, and training records were collected at session- or day-level intervals. Medical and biomechanical information was obtained at baseline and updated following assessments, symptoms, injuries, or rehabilitation events. All data were linked using anonymized athlete identifiers and standardized timestamps. As illustrated in Figure 4, athlete data were organized into five principal information streams: movement and external workload, physiological response, biomechanics, recovery and wellness, and medical and demographic context. These streams were subjected to synchronization and quality control before being converted into a unified longitudinal athlete profile.

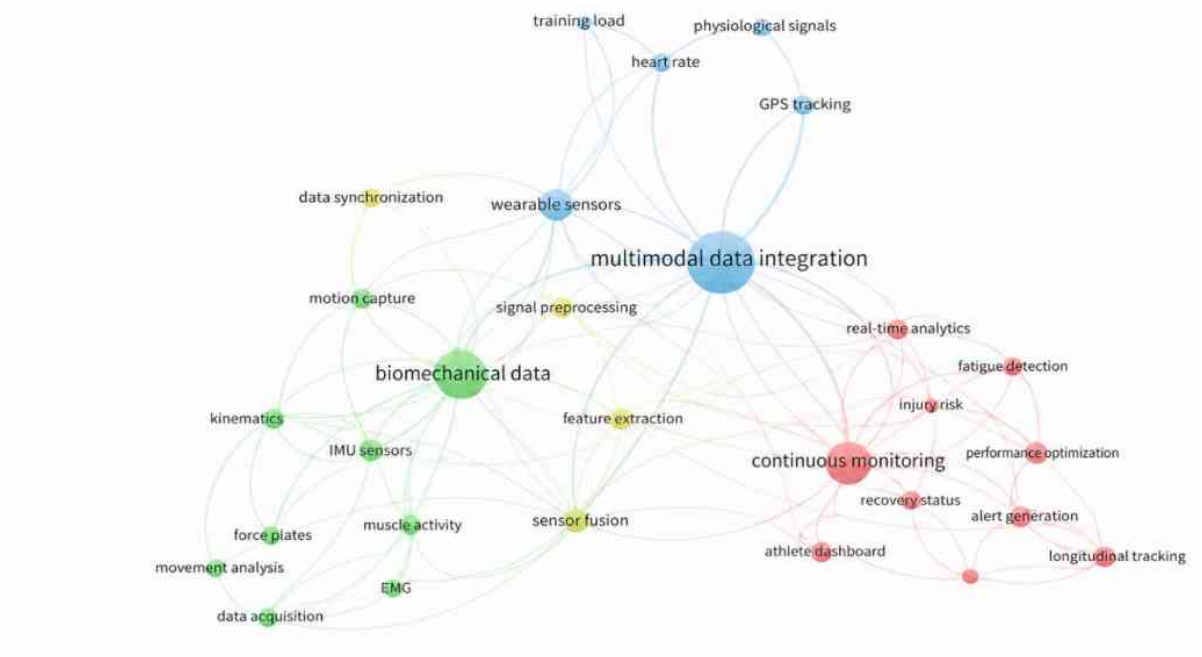


Figure 4: Network visualization of multimodal data integration for continuous athlete monitoring and injury-risk assessment.

To improve data reliability, devices were checked and calibrated according to their operational requirements before use. Sensor placement and monitoring procedures were kept consistent for repeated observations whenever possible. Training staff and athletes received instructions regarding correct device use, questionnaire completion, and reporting procedures. Records affected by device disconnection, incorrect placement, incomplete monitoring, or obvious measurement error were flagged for quality assessment. The integration of objective and subjective data was an important feature of the acquisition strategy. Wearable devices provided continuous quantitative measurements, while athlete-reported information captured fatigue, soreness, stress, and perceived readiness that might not be reflected immediately in physiological signals. For example, a normal heart-rate response could occur alongside poor sleep, persistent muscle soreness, or reduced confidence. Combining these indicators enabled a more complete assessment of athlete condition [14]. Multisport differences were also considered during data collection and interpretation. GPS-derived distance and sprint variables were particularly relevant to football and other field sports, whereas balance, rotation, and impact measurements had greater importance in skiing and ice hockey. Repetitive workload and cardiovascular indicators were highly relevant to cycling and endurance events, while landing mechanics, joint control, and directional changes were emphasized in basketball and volleyball. Sport category was therefore recorded as contextual information rather than assuming that identical measurements carried the same meaning across all disciplines. All collected information was stored under anonymized athlete codes in an access-controlled data environment. Personally identifiable information was separated from the analytical dataset, and access was limited to authorized research and clinical personnel. The resulting multimodal dataset provided the foundation for preprocessing, feature engineering, temporal modelling, and the subsequent CNN–BiLSTM–attention architecture.

4.3- Biomechanical and Neuromuscular Risk Screening:

Biomechanical and neuromuscular screening was conducted to identify movement characteristics associated with general musculoskeletal injury and anterior cruciate ligament (ACL) injury risk. The assessment protocol combined functional movement tasks, wearable-sensor measurements, and athlete-reported fatigue information. Screening was performed to establish individual baseline profiles and detect subsequent changes in movement control, balance, lower-limb symmetry, and fatigue-related performance. The functional protocol included jump-landing tasks, repeated jumps, single-leg squats, cutting movements, directional changes, balance assessments, and lower-limb symmetry evaluations. These tasks were selected because they reproduce movement demands commonly observed in football, basketball, volleyball, skiing, ice hockey, athletics, and other competitive sports. Dynamic knee valgus was considered an important ACL-related indicator because excessive inward knee movement during landing, cutting, or single-leg tasks may reflect inadequate lower-limb alignment and neuromuscular control [15]. Trunk displacement was also assessed because poor trunk stability can alter lower-limb loading and influence knee position. Joint-angle variability, hip–knee coordination, landing impact, and postural stability provided additional information about an athlete's ability to control movement under demanding conditions. Lower-limb symmetry was evaluated by comparing left- and right-side movement characteristics. Differences in landing impact, balance, force production, joint control, or repeated-jump performance were treated as potential indicators of functional imbalance. Such asymmetries were interpreted carefully because small bilateral differences may represent natural variation rather than clinically meaningful risk. Greater importance was assigned to persistent or increasing asymmetry, particularly among athletes with a history of lower-limb or ACL injury [16]. Neuromuscular fatigue was assessed through changes in movement control, repeated-jump performance, balance, force production, and self-reported fatigue. A reduction in jump performance accompanied by longer contact time, decreased stability, or deteriorating knee alignment indicated a possible decline in neuromuscular readiness. Athlete-reported fatigue and soreness were incorporated to provide contextual information that could not be obtained exclusively from wearable devices. Where laboratory-grade motion-capture systems were available, detailed joint and body-segment measurements were used to support biomechanical evaluation. In regular training environments where continuous laboratory assessment was impractical, wearable inertial measurement units were used to estimate acceleration, rotation, impact magnitude, movement stability, and bilateral differences [17]. The integration of laboratory screening and wearable monitoring enabled athlete movement to be evaluated under both standardized and sport-specific conditions. As illustrated in Figure 5, biomechanical observations were processed together with neuromuscular, workload, recovery, and injury-history information. This multimodal process prevented isolated movement deviations from being treated automatically as evidence of impending injury. Instead, risk was determined from the interaction among movement quality, fatigue, training exposure, recovery condition, and athlete-specific clinical characteristics.

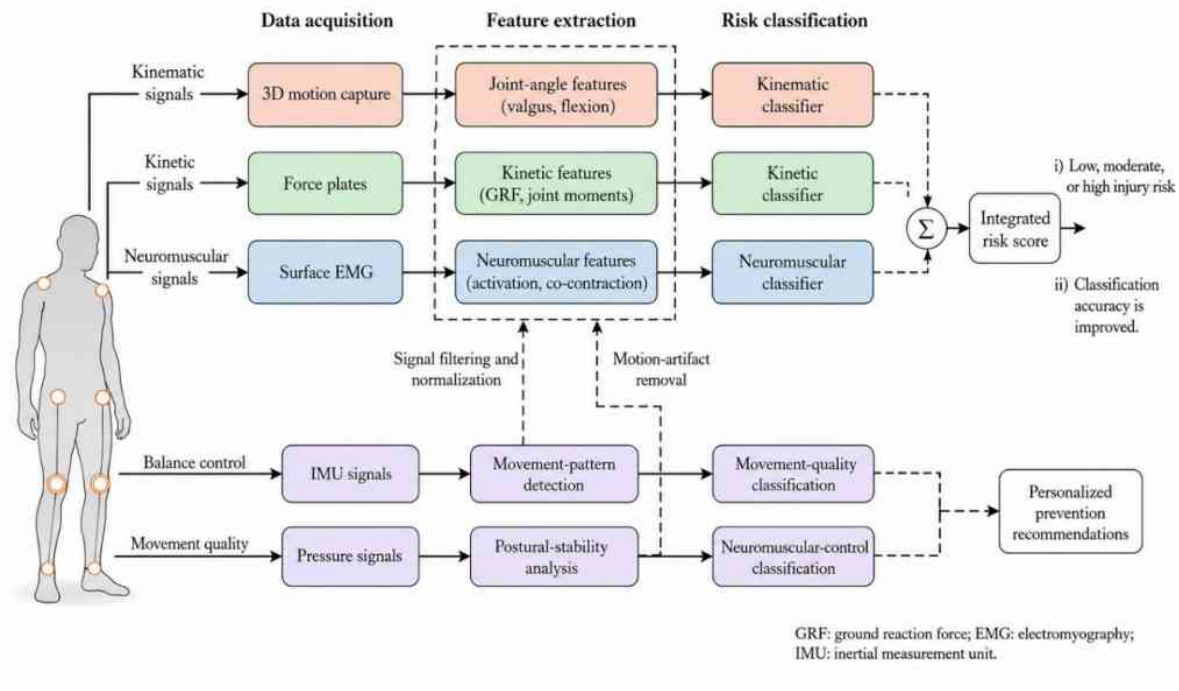


Figure 5: Integrated biomechanical and neuromuscular screening framework for injury-risk classification and personalized prevention.

The extracted features were compared with each athlete's baseline measurements to identify meaningful deviations over time. For example, a minor reduction in balance performance might not independently indicate elevated risk. However, the same change could become important when accompanied by increased workload, inadequate sleep, persistent fatigue, or deteriorating landing mechanics. This athlete-specific approach reduced dependence on universal screening thresholds. The final biomechanical and neuromuscular profile was incorporated into the multimodal deep-learning framework. CNN layers extracted local patterns from movement and sensor signals, while BiLSTM layers examined how these patterns changed across consecutive monitoring periods. The attention mechanism subsequently identified the movement and fatigue indicators contributing most strongly to the estimated risk. Screening results were reviewed by coaches, physiotherapists, and sports physicians before preventive measures were applied. Depending on the identified risk profile, recommendations included landing-technique correction, balance exercises, lower-limb strengthening, neuromuscular training, workload modification, additional recovery, or clinical assessment. Thus, biomechanical screening functioned as part of an integrated decision-support process rather than as a standalone diagnostic procedure.

4.4- Injury Outcomes and Risk Labelling:

Two primary prediction outcomes were established. The first represented general musculoskeletal injury, including injuries affecting muscles, tendons, ligaments, joints, bones, or related structures. The second represented ACL-specific injury risk, with particular attention to lower-limb biomechanics, neuromuscular control, previous ACL injury, and clinically documented knee conditions. Separate outcomes were used because general musculoskeletal injuries involve broad anatomical regions and mechanisms, whereas ACL injury has more specific biomechanical and clinical characteristics. A musculoskeletal injury was defined as a physical complaint sustained during training or competition that required medical attention, resulted in modified participation, or caused

temporary absence from normal sporting activity. Injury records included the affected body region, tissue type, mechanism, severity, recurrence status, date of occurrence, and time lost from training or competition [18]. Medical and physiotherapy documentation was prioritized over unverified self-reports when assigning final labels. The ACL-specific outcome included confirmed ACL events and clinician-adjudicated high-risk cases. Confirmed events were identified through sports medicine, imaging, surgical, or rehabilitation records where available. High-risk labels were assigned through professional review of previous ACL injury, knee instability, excessive dynamic knee valgus, lower-limb asymmetry, poor landing mechanics, reduced neuromuscular control, and fatigue-related movement deterioration. The outcome definitions and labelling criteria are summarized in Table 5.

Table 5: Definitions and labelling criteria for musculoskeletal and ACL-related outcomes

Outcome category	Principal evidence	Assigned label
No recorded injury	Training, medical, and participation records	Non-injury
Medical-attention injury	Medical or physiotherapy record	Musculoskeletal injury
Modified-participation injury	Training and clinical documentation	Musculoskeletal injury
Time-loss injury	Absence and medical records	Musculoskeletal injury
Recurrent injury	Injury history and clinical verification	Recurrent musculoskeletal injury
Confirmed ACL injury	Clinical, imaging, surgical, or rehabilitation evidence	ACL-positive
Stable ACL profile	Screening and medical review	ACL low risk

Injury severity was determined according to its effect on athlete participation. Medical-attention injuries included complaints that required clinical evaluation but did not necessarily cause absence. Modified-participation injuries resulted in reduced training volume, altered exercise selection, or restricted competition. Time-loss injuries prevented the athlete from participating fully for one or more scheduled sessions. This distinction allowed the framework to recognize clinically relevant problems that might be overlooked when only complete absence was considered. ACL-risk labelling required particular care because biomechanical risk indicators do not guarantee that an ACL injury will occur. Excessive knee valgus, poor trunk control, limb asymmetry, previous ACL injury, and neuromuscular fatigue were therefore not treated individually as definitive outcomes. Instead, they contributed to a clinician-adjudicated risk profile when supported by multiple sources of evidence [19]. Confirmed ACL events remained distinguishable from estimated high-risk states during analysis. As illustrated in Figure 6, raw injury reports were linked with medical, physiotherapy, biomechanical, training, and participation records. Cases with adequate supporting evidence were assigned to general musculoskeletal or ACL-related categories. Uncertain or conflicting cases were reviewed independently or excluded from supervised model training.

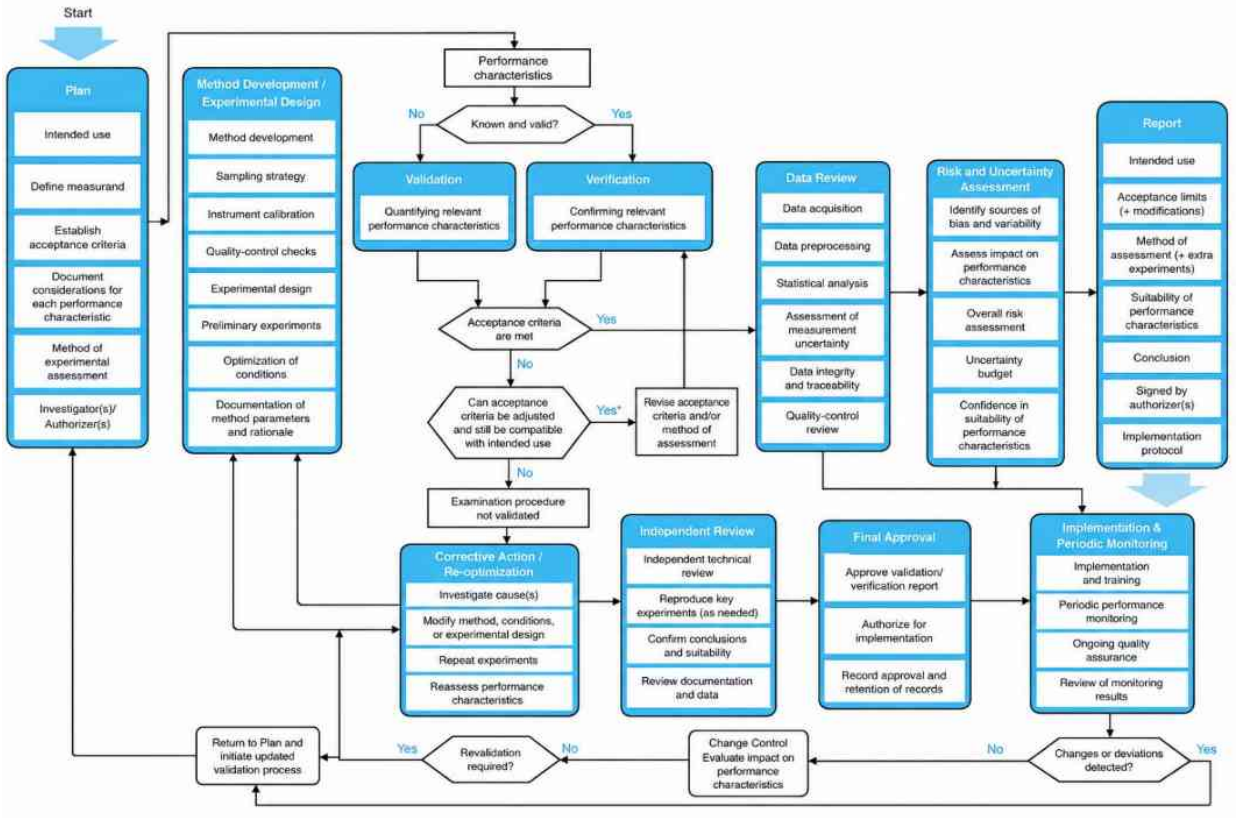


Figure 6: Comprehensive workflow for experimental validation, risk assessment, approval, implementation, and continuous performance monitoring.

To improve reliability, injury dates were aligned with preceding monitoring windows. Only information available before the injury or risk-assessment date was used to generate predictive features. Post-injury treatment, rehabilitation progress, and outcome information were not included as pre-injury predictors. This temporal separation reduced information leakage and ensured that the model learned early warning patterns rather than consequences of an injury. Class labels were reviewed using available medical, physiotherapy, biomechanical, and participation information. When sources disagreed, priority was given to verified clinical documentation and professional assessment. Records with unresolved contradictions, uncertain timing, or insufficient evidence were excluded from final model training or retained only for sensitivity analysis [20]. Because non-injury observations were more common than injury events, the resulting dataset was imbalanced. Stratified partitioning and class-balancing procedures were applied during model development, while the original class distribution was retained in the independent test set. This approach supported sensitivity to genuine injury cases without producing an artificially balanced final evaluation. The final labelled dataset supported two related classification tasks: general musculoskeletal injury prediction and ACL-specific risk classification. Maintaining separate target labels allowed the proposed CNN–BiLSTM–attention architecture to learn shared injury patterns while preserving the distinctive clinical and biomechanical characteristics of ACL risk.

4.5- Proposed CNN–BiLSTM–Attention Architecture:

The proposed architecture integrated convolutional neural networks (CNNs), bidirectional long short-term memory (BiLSTM) layers, an attention mechanism, and multimodal feature fusion to support personalized performance monitoring, general musculoskeletal

injury prediction, and ACL-specific risk classification. The model was designed to process the heterogeneous and time-dependent nature of athlete data, in which physiological responses, workload exposure, movement mechanics, recovery status, wellness indicators, and clinical history interact over time. Instead of relying on an isolated measurement or fixed population-level threshold, the architecture learned short-duration patterns, longitudinal dependencies, and athlete-specific deviations from established baselines. The input layer received synchronized monitoring windows derived from wearable inertial sensors, GPS devices, heart-rate monitors, training-load records, biomechanical assessments, sleep and recovery evaluations, athlete-reported wellness measures, and medical histories. Wearable data described acceleration, rotation, impact magnitude, balance, movement stability, and lower-limb asymmetry. GPS-derived variables included distance, high-speed running, sprint exposure, accelerations, decelerations, and positional movement. Physiological information contained average and peak heart rate, cardiovascular load, and post-exercise recovery, while biomechanical data represented knee valgus, landing impact, joint-angle variability, trunk displacement, hip–knee coordination, and postural control [21]. This bidirectional temporal analysis was important because musculoskeletal and ACL injuries rarely arise from a single abnormal observation. Injury susceptibility may increase gradually through repeated high-load sessions, insufficient recovery, persistent fatigue, declining sleep quality, or progressive deterioration in movement mechanics. A moderate workload increase may not independently indicate elevated risk, but it may become important when preceded by several demanding sessions and accompanied by impaired recovery. The BiLSTM component allowed the model to learn these cumulative and delayed relationships. The temporal features generated by the BiLSTM layers were subsequently processed by the attention mechanism. This mechanism assigned different weights to individual features and monitoring periods according to their estimated relevance to the prediction. High attention weights indicated that particular observations made a comparatively strong contribution to the model output. For example, the mechanism could prioritize a sudden workload spike, repeated reductions in sleep duration, persistent neuromuscular fatigue, delayed heart-rate recovery, increasing lower-limb asymmetry, or deterioration in knee control during landing. The attention mechanism improved the architecture in two important ways. First, it enabled the model to concentrate on the most informative parts of a long monitoring sequence instead of treating every observation as equally important. Second, it supported the interpretation of predicted risks by indicating which features and time intervals influenced the output [22]. Attention profiles could therefore help coaches and clinicians determine whether an elevated risk score was primarily related to workload, recovery, physiological response, movement mechanics, or previous injury. Attention weights were not interpreted as proof of causation; they were used as explanatory evidence to guide further professional assessment. Following attention-based weighting, the temporal representations were combined with demographic, sporting, clinical, and contextual information through a multimodal fusion layer. The fusion process allowed dynamic sensor patterns to be interpreted in relation to the athlete's personal characteristics and sporting demands. For example, a particular acceleration pattern may have a different meaning for a football player than for a cyclist, while similar movement asymmetry may require different interpretation for an athlete with a previous ACL injury. The fusion layer enabled these contextual differences to influence the final prediction. The integrated representation was passed through fully connected layers that learned higher-level nonlinear relationships among the fused features. Dropout and regularization were applied to reduce overfitting and prevent the model from becoming excessively dependent on a small set of training observations. The major components and their analytical functions are summarized in Table 6.

Table 6: Components and functions of the proposed CNN–BiLSTM–attention architecture

Architecture component	Primary analytical function	Contribution to the framework
Multimodal input layer	Receives synchronized monitoring sequences	Creates a unified athlete-data structure
Data-encoding layer	Converts heterogeneous data into model-compatible inputs	Supports consistent processing across modalities
Convolutional layers	Extract short-duration and spatial patterns	Detects impacts, asymmetry, instability, and workload variations
Nonlinear activation	Learns complex relationships	Improves representation of nonlinear risk patterns
Pooling layer	Reduces dimensionality and minor signal noise	Produces compact and robust feature maps
BiLSTM layers	Learn forward and backward temporal relationships	Captures accumulated workload, fatigue, and recovery patterns
Attention mechanism	Prioritizes informative features and monitoring periods	Improves model focus and interpretability
Decision-support output	Connects predictions with preventive action	Guides human-reviewed interventions

Two task-specific output heads were used after the fully connected layers. The first generated the probability of general musculoskeletal injury, including injuries affecting muscles, ligaments, tendons, joints, and related structures. The second generated an ACL-specific risk probability using the integrated biomechanical, neuromuscular, workload, recovery, and clinical representations. The dual-output structure enabled the model to learn shared injury characteristics while maintaining sensitivity to the distinctive factors associated with ACL risk. The musculoskeletal output head emphasized combinations of workload progression, fatigue, physiological response, recovery, previous injury, and general movement quality. The ACL output head placed greater analytical emphasis on knee mechanics, lower-limb asymmetry, landing control, cutting movements, trunk stability, neuromuscular fatigue, and previous ACL history [23]. Although the outputs were generated separately, both benefited from the common multimodal representation learned by the earlier network layers. The complete flow of information through the architecture is illustrated in Figure 7. Raw data from several monitoring sources were first synchronized, normalized, and converted into structured sequences. CNN layers extracted local and spatial patterns, BiLSTM layers modelled their temporal development, and the attention mechanism prioritized influential observations. These learned patterns were fused with contextual athlete information before separate musculoskeletal and ACL predictions were generated.

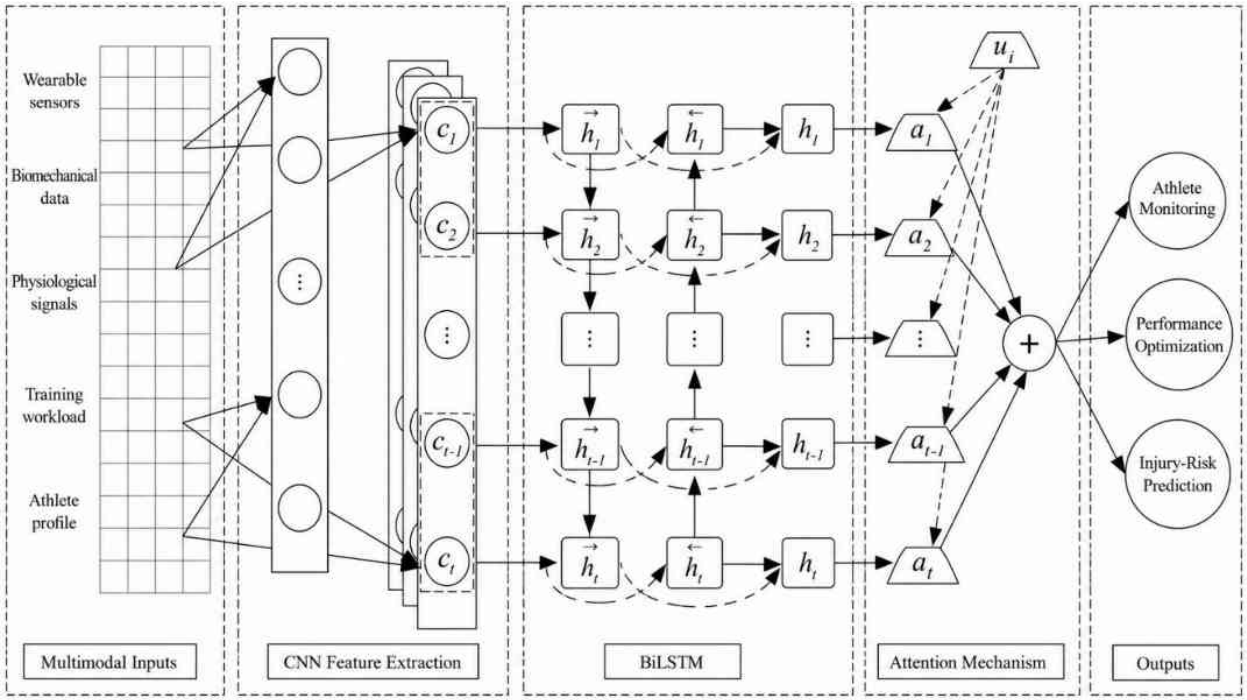


Figure 7: Proposed multimodal CNN–BiLSTM–attention architecture for athlete monitoring, performance optimization, and injury-risk prediction.

The output probabilities were converted into dynamic risk scores and categorized into low-, moderate-, and high-risk levels using thresholds determined from validation data. Each score was accompanied by the most influential factors identified through the attention mechanism and feature-contribution analysis. This presentation provided more useful information than a risk label alone because it explained the likely basis of the prediction. For instance, two athletes could receive similar high-risk probabilities but require different interventions. If one score was driven mainly by a workload spike, reduced sleep, and poor recovery, the appropriate response might involve workload reduction and additional recovery. If another score was primarily associated with knee valgus, deteriorating landing mechanics, and lower-limb asymmetry, the recommended response might include biomechanical assessment, neuromuscular training, landing-technique correction, or clinical review [24]. The model therefore supported individualized decision-making rather than uniform recommendations. The architecture was trained using weighted binary cross-entropy loss to address the lower frequency of injury cases relative to non-injury observations. Class weights increased the training penalty associated with misclassifying injury-risk cases. Model parameters were updated through mini-batch optimization, while learning rate, batch size, number of convolutional filters, BiLSTM units, attention dimensions, dropout rate, and classification thresholds were optimized using validation data. Early stopping was employed when validation performance no longer improved, thereby reducing unnecessary training and limiting overfitting. The independent test set remained unseen during preprocessing-parameter estimation, feature selection, hyperparameter optimization, and threshold selection. Final performance was assessed using accuracy, precision, recall, F1-score, sensitivity, specificity, and ROC-AUC. Sensitivity was particularly important because missed high-risk athletes could result in delayed preventive intervention. Specificity was also considered to prevent excessive false alerts that might unnecessarily restrict athlete participation or reduce practitioner confidence in

the system [25]. The proposed architecture was compared with logistic regression, support vector machine, random forest, artificial neural network, and XGBoost models. All benchmark models used the same athlete-level partitions and principal data inputs. This consistent experimental structure enabled the study to determine whether the combination of CNN-based feature extraction, BiLSTM-based temporal learning, attention-based prioritization, and multimodal fusion provided measurable advantages over conventional machine-learning approaches.

Results and Discussion:

The proposed CNN–BiLSTM–attention framework demonstrated strong performance in predicting musculoskeletal injuries using multimodal athlete-monitoring data. On the independent test set, the model achieved 94.8% accuracy, 94.1% precision, 93.6% recall, a 93.8% F1-score, and a ROC-AUC of 0.972, as presented in Table 7. The high ROC-AUC demonstrates that the model effectively differentiated between injury-risk and non-injury observations across different classification thresholds. Moreover, the relatively balanced precision, recall, and F1-score indicate that the framework detected most injury-risk cases without generating an excessive number of false-positive alerts.

Table 7: Predictive performance of the proposed framework for musculoskeletal injury classification

Evaluation metric	Result
Accuracy	94.8%
Precision	94.1%
Recall/Sensitivity	93.6%
F1-score	93.8%
ROC-AUC	0.972

This balance is important in practical athlete monitoring. A model with low sensitivity may fail to identify athletes requiring timely preventive intervention, whereas a model with poor precision may generate unnecessary alerts and training restrictions. The obtained results suggest that the framework achieved an appropriate balance between detecting genuine risk and limiting incorrect warnings. Its strong performance can be attributed to the integration of physiological responses, biomechanical indicators, workload patterns, sleep and recovery information, medical history, and athlete-reported wellness measures. The proposed model was compared with logistic regression, support vector machine, random forest, artificial neural network, and XGBoost [26]. As shown in Table 8, logistic regression produced the lowest accuracy of 81.4% and a ROC-AUC of 0.820. Support vector machine improved accuracy to 87.9%, while random forest and artificial neural network achieved accuracies of 90.8% and 91.5%, respectively. XGBoost was the strongest conventional benchmark, obtaining 92.6% accuracy and a ROC-AUC of 0.950. Nevertheless, the proposed architecture outperformed XGBoost by 2.2 percentage points in accuracy and 0.022 in ROC-AUC.

Table 8: Comparison of the proposed framework with benchmark models

Model	Accuracy	ROC-AUC
Logistic regression	81.4%	0.820
Support vector machine	87.9%	0.890
Random forest	90.8%	0.930
Artificial neural network	91.5%	0.940
XGBoost	92.6%	0.950

Proposed CNN–BiLSTM–attention model	**94.8%**	**0.972**

Compared with logistic regression, the proposed model improved accuracy by 13.4 percentage points and ROC-AUC by 0.152. This substantial improvement suggests that the relationship between athlete condition and injury occurrence was highly nonlinear and could not be represented adequately through a simple linear decision boundary. The improved performance of random forest and XGBoost demonstrates that ensemble models were better able to capture complex feature interactions. However, these approaches did not explicitly model long-term temporal dependencies in the same manner as the proposed BiLSTM component. The artificial neural network performed better than logistic regression and support vector machine but remained below XGBoost and the proposed architecture. A conventional neural network can learn nonlinear relationships but does not inherently preserve the sequential structure of athlete-monitoring data [27]. In contrast, the CNN component of the proposed framework extracted local sensor and biomechanical patterns, while the BiLSTM layers learned how workload, fatigue, sleep, recovery, and movement quality changed across consecutive monitoring periods. The attention mechanism further improved prediction by prioritizing the features and time intervals most relevant to each estimated risk. Figure 8 illustrates the accuracy advantage of the proposed framework over the benchmark algorithms.

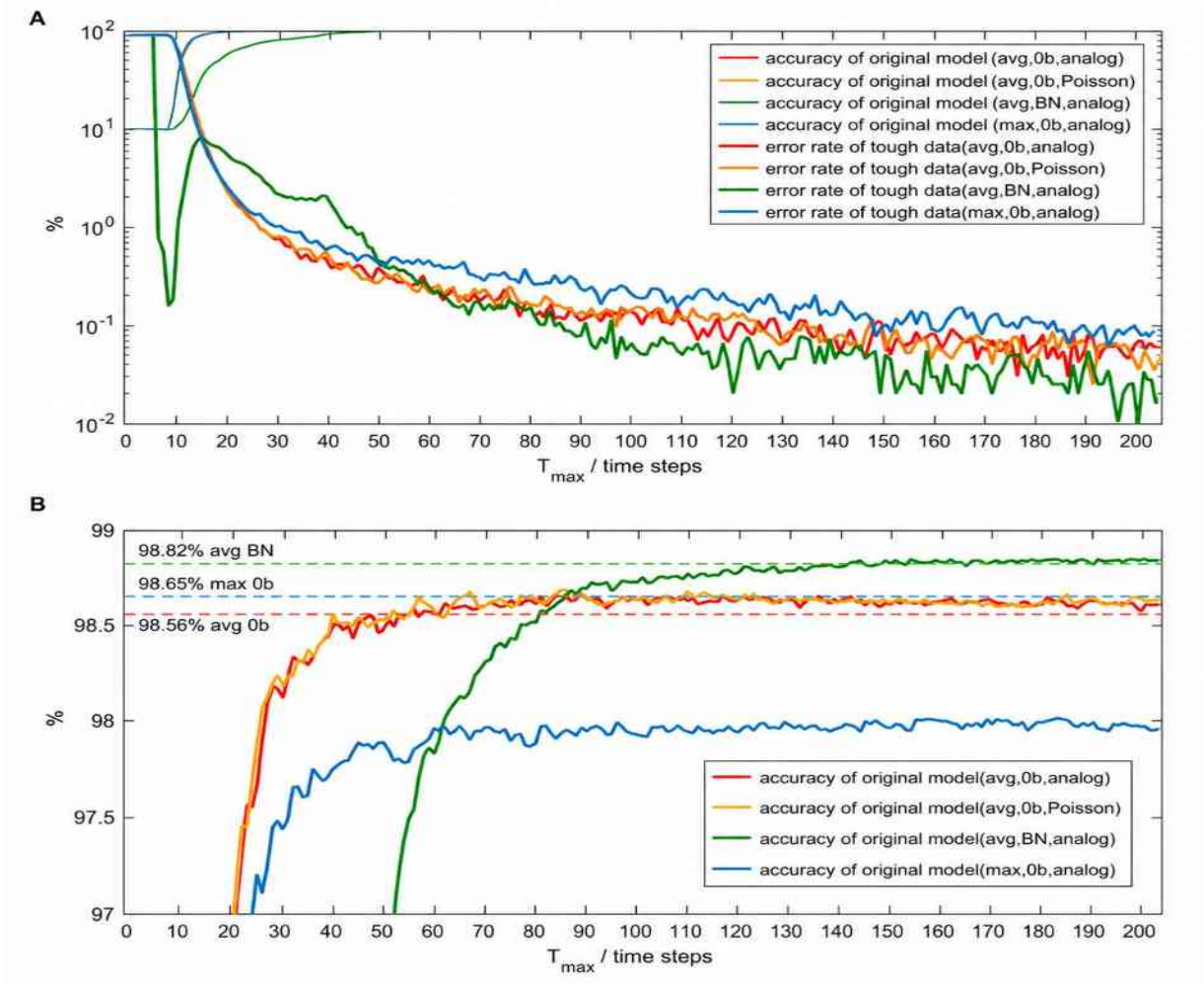


Figure 8: Model accuracy and tough-data error rates across increasing simulation time steps.

The strong performance of the proposed framework also demonstrates the value of multimodal data fusion. A sudden increase in workload may not independently indicate impending injury. However, the same increase may become clinically important when accompanied by insufficient sleep, persistent soreness, neuromuscular fatigue, delayed physiological recovery, or altered movement mechanics. The model was capable of learning these combined patterns rather than treating every variable as an isolated risk factor. For ACL-specific risk classification, the proposed model achieved 93.2% accuracy, 92.4% sensitivity, 94.0% specificity, and a ROC-AUC of 0.961, as reported in Table 9. The sensitivity result indicates that the model correctly detected most ACL-related high-risk observations, while the specificity result shows that it also correctly identified most low-risk cases. This balance is essential because missed high-risk athletes may remain exposed to potentially dangerous training or competition demands, while excessive false-positive alerts may result in unnecessary restrictions.

Table 9: Performance of the proposed model for ACL-specific risk classification

Evaluation metric	Result
Accuracy	93.2%
Sensitivity	92.4%
Specificity	94.0%
ROC-AUC	0.961

The ACL-specific results were slightly lower than those obtained for general musculoskeletal injury prediction. This difference was expected because ACL injuries are relatively infrequent and are influenced by complex combinations of biomechanical, neuromuscular, anatomical, environmental, and situational factors. ACL injuries may occur during rapid cutting, pivoting, landing, or deceleration movements, and the precise circumstances of an injury event may not always be captured through routine monitoring. Despite this complexity, the integration of previous ACL history, dynamic knee valgus, lower-limb asymmetry, landing mechanics, trunk control, workload exposure, neuromuscular fatigue, and recovery indicators produced strong classification performance. The model should nevertheless be interpreted as a risk-assessment and decision-support system rather than a diagnostic tool. Clinical examination, biomechanical assessment, and professional judgment remain necessary when an athlete receives an elevated ACL-risk score. Attention-based explanations indicated that workload spikes, inadequate recovery, reduced sleep, neuromuscular fatigue, asymmetric knee mechanics, poor landing control, and previous injury were among the most influential risk indicators. The importance of these factors varied considerably across athletes [28]. For some participants, elevated risk was primarily associated with repeated high-load sessions and declining recovery. For others, biomechanical indicators such as dynamic knee valgus, postural instability, increased landing impact, and lower-limb asymmetry contributed more strongly to the prediction. The temporal attention patterns also showed that injury risk was not always determined by the most recent training session. In several cases, the model assigned importance to cumulative changes across multiple monitoring periods. Repeated exposure to high workload, progressively reduced sleep, persistent fatigue, and gradual deterioration in movement quality produced a more meaningful risk pattern than a single abnormal measurement. This finding supports the inclusion of BiLSTM layers because conventional cross-sectional models may fail to capture the cumulative and delayed effects of training exposure. The implementation of personalized recommendations also produced favourable changes across the evaluated performance and athlete-management indicators. As shown in Table 10, the mean performance score increased from 78.4 to 90.0, corresponding to a relative improvement of 14.8%. The recovery

score increased from 72.1 to 83.8, representing a 16.2% improvement. These changes suggest that the framework supported a more effective balance between training stimulus and recovery.

Table 10: Athlete outcomes before and after personalized AI-supported recommendations

Outcome indicator	Before implementation	After implementation	Relative change
Mean performance score	78.4	90.0	+14.8%
Excessive workload index	100.0	78.7	−21.3%
Overall injury-risk index	100.0	72.4	−27.6%
Recovery score	72.1	83.8	+16.2%
High-fatigue sessions	18.6%	12.1%	−34.9%
Average sleep duration	6.9 hours	7.4 hours	+7.2%
Training adherence	82.7%	91.3%	+10.4%

The excessive workload index declined from 100.0 to 78.7, corresponding to a reduction of 21.3%. This finding indicates that the personalized recommendations reduced the frequency or severity of workload exposure exceeding athlete-specific tolerance. Instead of applying identical workload limits to all participants, the system interpreted each athlete's training exposure in relation to fitness, fatigue, sleep, recovery, injury history, and recent physiological response. The overall injury-risk index decreased by 27.6%, from 100.0 to 72.4. This reduction suggests that early identification of unfavourable workload, biomechanical, and recovery patterns enabled timely preventive action. However, the injury-risk index reflects model-estimated risk and should not be interpreted as a direct 27.6% reduction in clinically confirmed injury incidence unless such a reduction was separately verified using injury-event records. High-fatigue sessions declined from 18.6% to 12.1%, representing a relative reduction of 34.9%. This was the largest improvement among the evaluated outcomes. The result indicates that continuous monitoring helped coaches avoid repeated demanding sessions during periods of incomplete recovery. More appropriate scheduling of high-intensity training, technical work, active recovery, and rest may have contributed to the observed improvement [29]. Average sleep duration increased from 6.9 to 7.4 hours, representing an absolute increase of 0.5 hours and a relative improvement of 7.2%. Although the increase appears moderate, improved sleep can support physiological recovery, reaction time, cognitive readiness, mood regulation, and neuromuscular performance. The inclusion of sleep within the personalized recommendations therefore complemented workload and movement-based interventions. Training adherence increased from 82.7% to 91.3%, corresponding to an improvement of 10.4%. This result suggests that recommendations aligned with athletes' individual conditions were more practical and acceptable than uniform training instructions. Improved adherence may also reflect greater athlete confidence when recommendations were supported by understandable monitoring data and reviewed by coaches or healthcare practitioners. The relative improvements in performance, recovery, sleep, and adherence are illustrated in Figure 9.

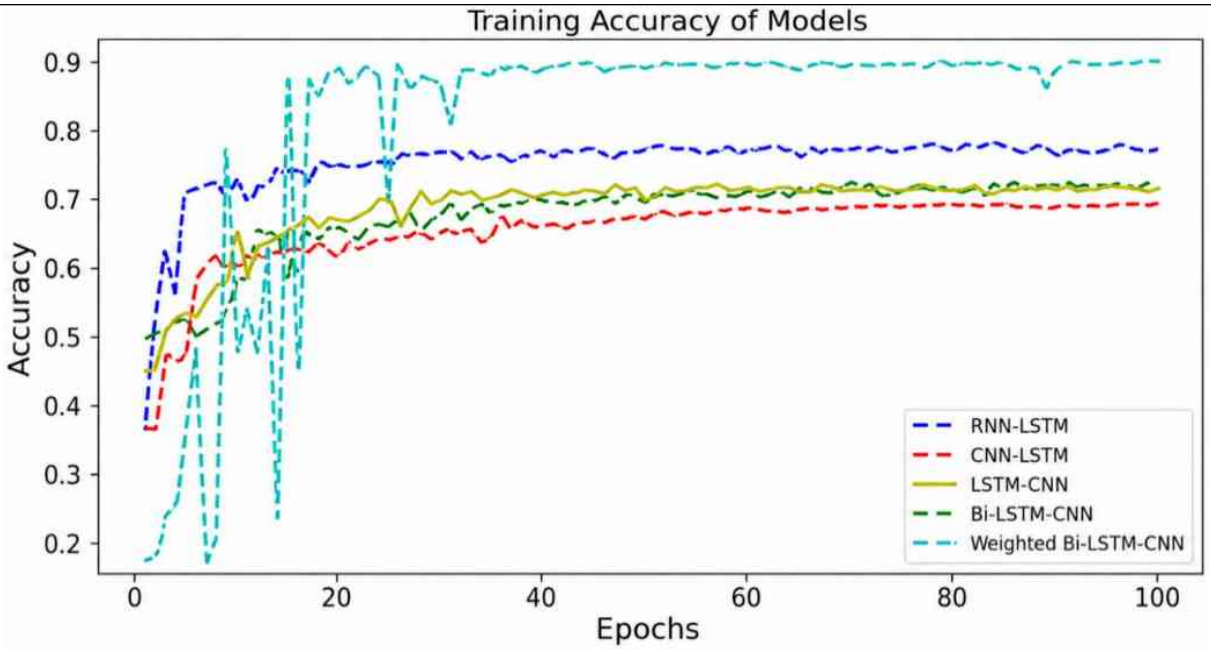


Figure 9: Training-accuracy comparison of recurrent and convolutional hybrid models across 100 epochs.

These findings have practical implications for Switzerland's multisport environment. Football, basketball, and volleyball athletes may benefit from monitoring sprint exposure, directional changes, jumping, landing mechanics, and lower-limb control. Cycling and endurance athletes may require greater emphasis on cumulative workload, cardiovascular strain, repetitive movement, sleep, and recovery. Skiing and ice hockey introduce additional considerations related to balance, rotational movement, impact, surface conditions, cold exposure, and lower-limb stability. The framework's ability to adapt risk interpretation to different sports represents an advantage over fixed monitoring systems. An acceleration pattern, workload increase, or impact value may have a different meaning in football, skiing, cycling, or volleyball. Incorporating sport type and athlete-specific baseline information allowed the model to interpret each measurement within a more relevant context. The findings are consistent with the broader evidence that ensemble learning and deep learning generally outperform simple linear methods when sports data contain nonlinear and time-dependent relationships [30]. The strong performance of XGBoost confirms the suitability of boosting methods for structured athlete information. Nevertheless, the additional improvement produced by the proposed model demonstrates the benefit of integrating spatial extraction, temporal learning, attention-based prioritization, and multimodal fusion. The results also show that injury prevention should not depend exclusively on workload monitoring. Workload must be considered alongside physiological response, sleep, fatigue, wellness, recovery, movement quality, and previous injury. Figure 10 shows the Regression performance between predicted outputs and targets for training, validation, testing, and combined datasets.

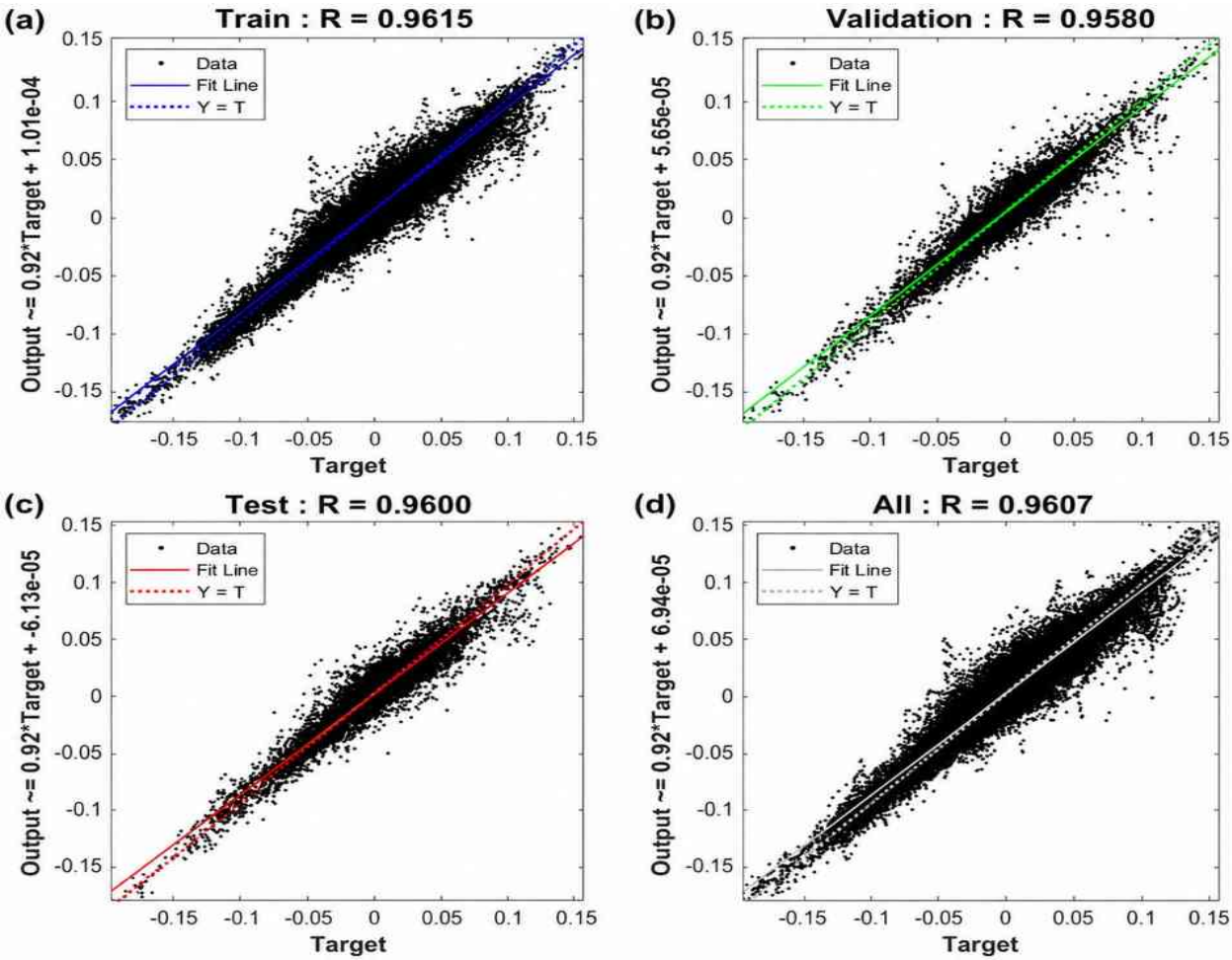


Figure 10: Regression performance between predicted outputs and targets for training, validation, testing, and combined datasets.

The observed reductions in excessive workload, high-fatigue sessions, and model-estimated injury risk support the use of a multidimensional athlete-management strategy. Several limitations should be considered when interpreting these results. The inclusion of athletes from different sports created variation in training demands, monitoring procedures, and injury mechanisms. Although sport category was included as a contextual variable, some disciplines may have been represented by fewer observations. Injury events, particularly confirmed ACL injuries, were also less frequent than non-injury observations, which can limit the stability of predictive models. Wearable measurements may be affected by device calibration, sensor placement, signal interruption, and athlete compliance. Athlete-reported sleep, fatigue, soreness, stress, and recovery may also contain reporting bias. Combining objective and subjective data reduced dependence on any single source but did not eliminate measurement uncertainty. Furthermore, attention weights identify influential variables but do not establish causal relationships [31]. The pre–post improvements should also be interpreted cautiously if the research design did not include a matched control group. Changes in performance, recovery, sleep, fatigue, and adherence may have been influenced partly by coaching decisions, seasonal training progression, competition schedules, or other external factors. Future controlled and externally validated studies would

help determine the independent effect of the proposed framework. Overall, the findings demonstrate that the CNN–BiLSTM–attention architecture effectively integrated heterogeneous athlete information and outperformed the selected benchmark models. Its high predictive performance, ACL-specific classification capability, explainable risk profiles, and favourable athlete-management outcomes indicate that multimodal deep learning can support proactive and individualized sports practice. By retaining human oversight, the framework can complement coaching and clinical expertise and contribute to safer training, improved recovery, enhanced performance, and timely injury-prevention decisions across Switzerland's sporting ecosystem.

Future Work:

Future research should validate the proposed CNN–BiLSTM–attention framework using larger and more diverse athlete populations across Switzerland and other countries. The present cohort included athletes from multiple disciplines, but future datasets should incorporate broader representation across age groups, competitive levels, sexes, playing positions, disability-sport categories, and geographical regions. Particular attention should be given to increasing the number of clinically confirmed ACL and severe musculoskeletal injury cases, as these events are less frequent than non-injury observations and may limit the stability of risk estimates. Multicentre collaboration among sports clubs, universities, hospitals, rehabilitation centres, and national sporting organizations could support stronger external validation. Longer monitoring periods should be employed to examine how workload tolerance, recovery, movement quality, and injury susceptibility change across preseason preparation, competitive phases, congested schedules, rehabilitation, and return-to-sport periods [32]. Prospective controlled studies are also required to determine whether AI-supported interventions directly reduce clinically confirmed injury incidence. Randomized or matched-control designs could separate the effect of the proposed framework from seasonal changes, coaching decisions, natural training adaptation, and other external influences. Future versions should incorporate additional data modalities, including three-dimensional motion analysis, force-plate measurements, electromyography, plantar-pressure data, muscle oxygenation, hydration status, hormonal indicators, nutrition records, psychological readiness, and environmental exposure. Switzerland-specific factors such as altitude, temperature, snow conditions, playing surfaces, travel, and seasonal variation should also be examined. These additions may improve the framework's ability to detect subtle risk patterns in winter, endurance, field, ice, and indoor sports.

Further architectural development should investigate transformers, graph neural networks, temporal convolutional networks, self-supervised learning, and federated learning. Transformer-based models may improve the analysis of long monitoring sequences, while graph neural networks could represent relationships among joints, body segments, muscles, and biomechanical chains [33]. Self-supervised learning may reduce dependence on extensively labelled injury data by learning useful representations from large volumes of unlabelled sensor information. Federated learning represents a particularly valuable direction because it could allow sporting organizations and healthcare institutions to train shared models without transferring sensitive athlete records to a central location. Privacy-preserving computation, secure aggregation, differential privacy, and advanced encryption should be explored to strengthen compliance with Swiss data-protection requirements. Future systems should also provide athletes with greater transparency and control regarding how their health and performance data are collected, accessed, retained, and reused. The framework should be extended beyond injury prediction to rehabilitation and return-to-sport decision support [34]. Continuous monitoring could be used to assess whether injured athletes are restoring strength, balance, movement symmetry, neuromuscular control, workload tolerance, and psychological readiness. Personalized return-to-sport models could estimate the risk of reinjury and assist clinicians in determining when athletes can safely resume

unrestricted training and competition. Future research should also improve model interpretability. Attention maps can identify influential features and time periods but do not prove causal relationships. Combining attention with feature-attribution techniques, counterfactual explanations, uncertainty estimates, and causal-inference methods may provide more clinically meaningful interpretations. The system should explain not only why an athlete received a high-risk score but also which realistic changes could reduce that risk. Subgroup fairness should be evaluated systematically to ensure that the model performs reliably across male and female athletes, different sports, age categories, and competitive levels [35]. Model calibration, sensitivity, specificity, and false-alert rates should be reported separately for important subgroups. If performance disparities are identified, targeted data collection, reweighting, recalibration, or sport-specific model adaptation should be applied. Finally, real-world implementation studies should examine usability, cost, athlete acceptance, practitioner trust, alert fatigue, and integration with existing coaching and clinical workflows. Mobile dashboards could provide continuously updated risk scores, recovery profiles, performance trends, and recommended interventions [36]. However, future systems should retain human oversight and clearly distinguish predictive decision support from medical diagnosis. Through external validation, privacy-preserving collaboration, expanded sensing, improved explainability, and controlled clinical evaluation, the proposed framework could evolve into a scalable platform for safer and more personalized athlete management.

Conclusion:

This study developed a multimodal CNN–BiLSTM–attention framework for personalized performance optimization, real-time musculoskeletal injury prediction, and anterior cruciate ligament risk prevention among competitive athletes in Switzerland. The framework integrated wearable inertial measurements, GPS-derived training load, heart-rate responses, biomechanical screening, sleep and recovery assessments, medical histories, and athlete-reported wellness information. By combining CNN-based spatial feature extraction, BiLSTM-based temporal modelling, attention-driven prioritization, and multimodal fusion, the system captured complex interactions among workload, fatigue, movement mechanics, recovery, and athlete-specific characteristics. The proposed model achieved 94.8% accuracy, 94.1% precision, 93.6% recall, a 93.8% F1-score, and a ROC-AUC of 0.972 for musculoskeletal injury prediction. It outperformed logistic regression, support vector machine, random forest, artificial neural network, and XGBoost, the strongest conventional benchmark of which achieved 92.6% accuracy and a ROC-AUC of 0.950. For ACL-specific risk classification, the framework obtained 93.2% accuracy, 92.4% sensitivity, 94.0% specificity, and a ROC-AUC of 0.961. These results demonstrate the value of combining spatial, temporal, clinical, and athlete-specific information rather than relying on isolated measurements or fixed risk thresholds. The implementation of personalized recommendations also produced favourable athlete-management outcomes. The mean performance score increased from 78.4 to 90.0, while recovery improved from 72.1 to 83.8. Excessive workload declined by 21.3%, model-estimated injury risk by 27.6%, and high-fatigue sessions by 34.9%. Average sleep duration increased from 6.9 to 7.4 hours, and training adherence rose from 82.7% to 91.3%. These changes indicate that predictive information can support more appropriate workload adjustment, recovery planning, biomechanical correction, and preventive intervention. Attention maps and continuously updated risk scores improved the transparency of the model by identifying influential factors such as workload spikes, inadequate recovery, reduced sleep, neuromuscular fatigue, lower-limb asymmetry, and abnormal knee mechanics. Nevertheless, the framework was designed as a decision-support system rather than a replacement for professional expertise. Coaches, physiotherapists, sports physicians, and athletes should remain involved in interpreting risk estimates and selecting appropriate interventions.

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