Guarding the Game: Deep Neural Networks in Athlete Injury Prediction

Ajith Raj Periyasamy

Kent State University

Advanced Machine Learning (BA-64061-001)

Dr. Chaojiang Wu

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Abstract

In current sports athletes show significant competitiveness, perform with intensity displaying increased physicality. Injury prevention is high priority across various athletic activities. Deep Neural Networks changed the field of injury prediction and monitoring through exact pattern recognition from complicated data like motion sequences, medical pictures as well as biometric signals. This study investigates the uses of different Deep Neural Network arrangements, like Convolution Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks and Deep Convolutional Autoencoders. The goal is to find risk indicators and to predict injuries in athletes. A wide look at ten new studies highlights steady growth in how correct injury detection is. Only few models attain prediction rates above 90 %. These models show high ability in regions like ACL injury diagnosis, movement review with wearable sensors in addition to EMG-based injury monitoring. Hybrid models that combine deep learning with semi-supervised clustering or time-series image encoding show good generalization across a range of sports injury kinds. Actual uses like live injury monitoring systems and cloud-based sports medicine setups, show the workability of the procedures. Despite the big forward steps, the field still has issues tied to data that does not match, it is hard to understand model behavior along with applying solutions on a big scale. This study puts together the latest findings. It also spots later paths, like adding explainable AI and multi-modal data fusion, to help athlete safety through active injury handling.

Keywords: sports injury prevention, injury monitoring, deep neural networks, injury risk assessment, deep learning in sports, convolution neural networks, recurrent neural networks

Guarding the Game: Deep Neural Networks in Athlete Injury Prediction

Injuries continue to be a big worry in sports. They affect athletic ability, how long a career lasts and also the potential success of a team. Common ways to stop injuries depend a lot on looking back at what happened and using normal training exercises. These methods often do not deal with the fact that injury dangers are specific to each person and always change. Artificial intelligence (AI), especially Deep neural networks (DNNs), is a major step forward in sports medicine. These models are good at finding complicated patterns inside big collections of information. This lets them predict injuries early, even before someone feels it (Ye et al., 2023).

Among these DNNs, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have made it much easier to understand difficult sports information. CNNs work especially well when looking at spatial information, such as pictures and videos. This makes them useful for monitoring athlete posture and movement. Using convolutional filters, they can spot unusual things in how an athlete moves, which can show a chance of injury (Wang et al., 2017). RNNs focus on information in a series. This lets them notice patterns in performance numbers over time. The ability to remember past data lets them look at series of actions and spot injury dangers by seeing patterns during an amount of time (Sato & Haegele, 2017).

Combined with wearable devices, DNNs allow constant observation. This gives quick feedback and helps with active care. Ren et al. (2024) displayed the actual advantages of such systems in activities such as aerobics and running. In those activities, constant information analysis made injury detection much more accurate. These advances point out how AI tools can change the ways to stop injuries.

Major problems continue to exist, despite all this. Differences in information sets, how hard it is to know what the models shows as well as the demand for a lot of relevant information are still obstacles. Resolving these concerns needs group work from different fields. This involves people who know a lot about sports science, data work together towards creating effective solutions.

This study explores the important role of deep neural networks in predicting and monitoring sports-related injuries. The text looks closely at current methods, checks their success in addition to spotting major problems. The main aim of the study is to explain how Artificial Intelligence can enhance athlete performance and well-being.

Literature Review

The literature review section aims to review the existing articles present on the topic of study. The goal of the review is to highlight how deep learning is being used in sports to predict athlete injuries based on the nature of the data being used. I decided to structure the section by grouping the current works into categories. The studies were grouped based on 2 broad categories. The basis of grouping was decided depending on the data type used as input for the analysis. One of the categories uses Wearable technology data, such as wearable sensor data (accelerometers, motion data, etc.) or structured time-series motion data for injury prediction using deep learning. The other category uses medical images (MRI, EMG signal images, or injury photos) and applies CNN-based deep learning models for diagnosis or injury localization.

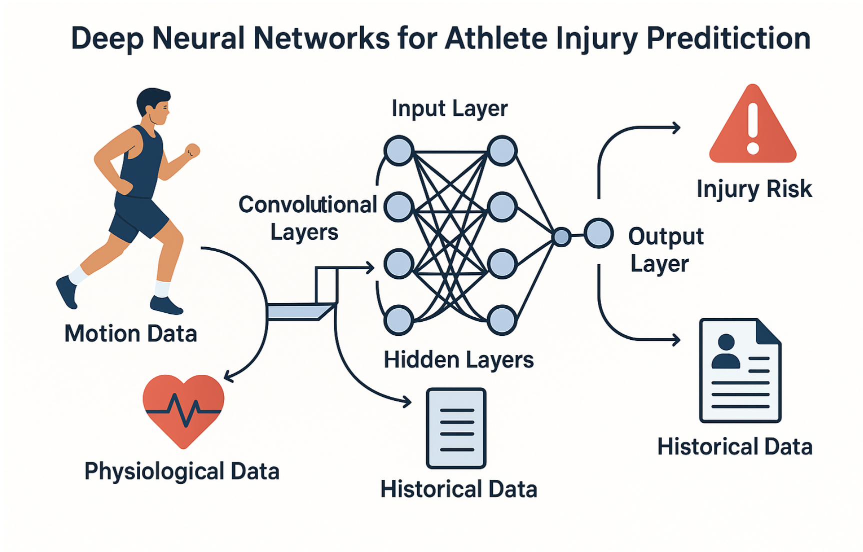

Figure 1

Wearable or motion-based inputs:

Latest Techniques

Sports injury prediction has advanced through deep learning models. Such models are often designed for motion sensor data and time-series recordings. The reviewed studies present different progressive methods, data acquisition, feature transformation along with predictive modeling using neural networks.

Ye et al. (2023) presented a detailed research study. It converts time-series sensor readings into images. The transformation uses techniques such as Gramian Angular Summation Field, Gramian Angular Difference Field, Markov Transition Field along with Recurrence Plots. This encoding captures sequential information in spatial form. It allows processing using a Deep Convolutional Autoencoder. After feature extraction, a Deep Neural Network classifier performs injury risk categorization. The method helps in pattern detection from temporal data.

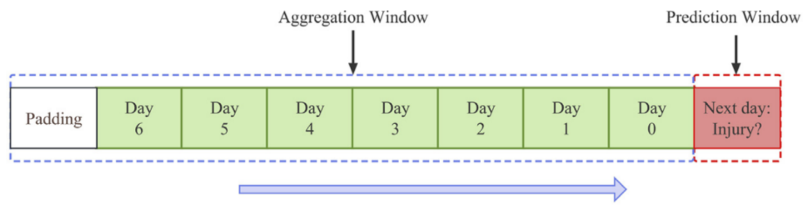

Figure 2 – Time-series encoding methods [GASF, GADF, MTF, RF] from (Research paper: A novel approach for sports injury risk prediction: based on time-series image encoding and deep learning by Ye et al., 2023.)

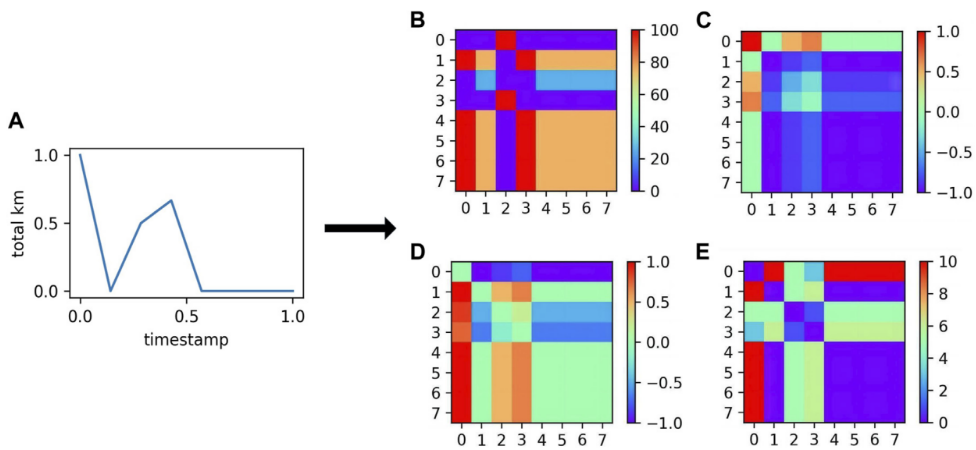

Figure 3 – Normalized time-series transformation from (Research paper: A novel approach for sports injury risk prediction: based on time-series image encoding and deep learning by Ye et al., 2023.)

Zhao and Li (2023) presented a combined deep learning and semi-supervised clustering structure. A supervised deep neural network was trained. The training data consisted of movement records from Functional Movement Screening tests. The tests contained exercises such as squats and hurdle steps. To make better use of data without labels, they added a semi-supervised clustering procedure. This improved the model's ability to apply learned information to new data. In addition, they put in place a feature sequence classification procedure. It used Bayesian filtering to make predictions better and to lower errors during classification.

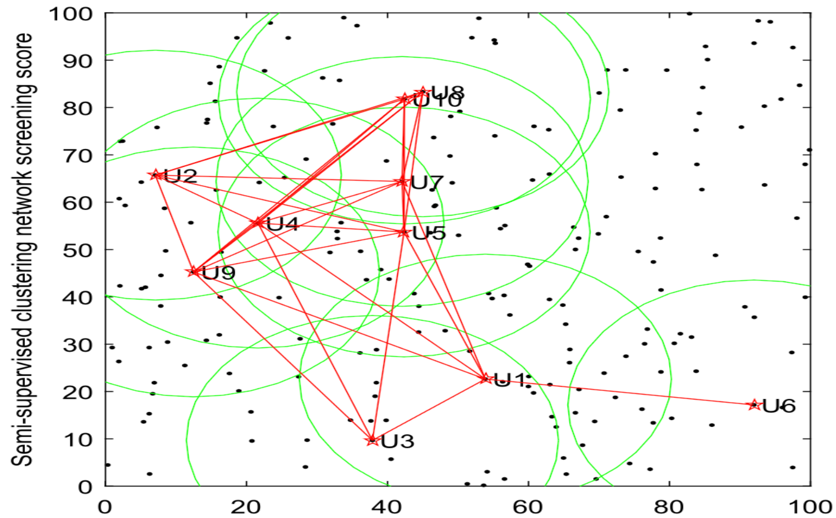

Figure 4 – Semi-supervised clustering network from (Research paper: A combined deep neural network and semi-supervised clustering method for sports injury risk prediction by Zhao and Li (2023).

Yang et al. (2024) built a predictive system. It used a Backpropagation (BP) Neural Network to identify athletic movements from sensor data. The design used a three-layer neural network. This network learned to differentiate between actions, such as running and standing. The learning used acceleration and gyroscopic information. The model focused on spotting motion patterns that show increased injury possibility.

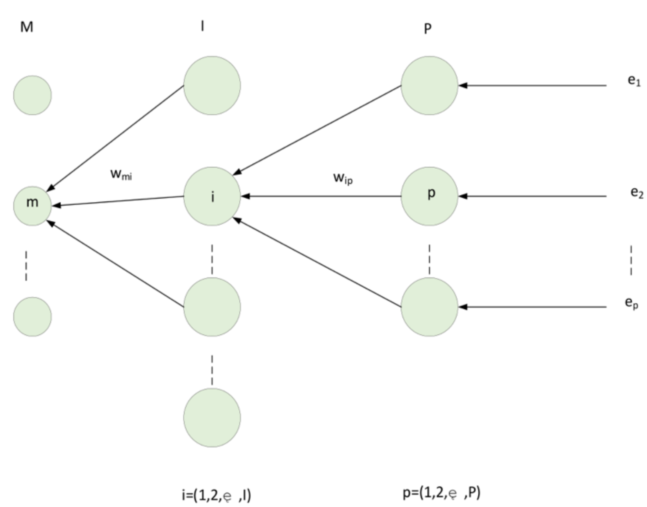

Figure 5 – BP Neural Network Architecture from (Research paper: Prediction and simulation of wearable sensor devices for sports injury prevention based on BP neural network by Yang et al., 2024.)

Sadr et al., (2023) used a deep neural network applied to unprocessed sequential sensor data. This eliminated the need for manual feature engineering. This method let the model learn relevant data for injury prediction by itself. It offered a benefit over older ways that used handcrafted features.

Effectiveness of the Techniques

Studies have shown deep learning models performing better than traditional techniques. Ye et al. (2023) noted their GASF-DCAE-DNN framework had a test **AUC of 0.891**, a **G-mean of 0.830**, **Sensitivity at 81.6 %** and **Specificity at 84.5 %**. This outcome suggests a classification between high plus low-risk athletes that had a good balance and could be counted on. Zhao and Li (2023) confirmed their model worked through establishing best cut-off values for the FMS system (15.5 for total male athletes, 16.5 for females). The model's classification performance was computed using the Receiver Operating Characteristic (ROC) Curve and the Youden Index. This indicates that the model was effective in distinguishing between different injury risk groups. Yang et al. (2024) saw their BP neural network worked best with 11 hidden neurons. This gave accuracy in action recognition. Sadr et al., (2023) conveyed that the deep learning model had a greater prediction skill when it was compared to common statistical models. Exact values were not given completely. Those results focus on the idea that feature extraction and classification by deep neural networks significantly improved the accuracy of injury risk prediction based on wearable motion data.

Challenges and Limitations

Despite the reported successes, several challenges were consistently identified:

- ***Dataset Size and Diversity***:

Ye et al. (2023) and Zhao and Li (2023) both showed that they worked with small athlete samples. This creates worries about model overfitting. Generalization to larger populations is difficult.

- ***Data Imbalance***:

Datasets about injuries often have uneven distributions. There are many records without injuries, but fewer records of injury events. This makes model training harder. Ye et al. (2023) handled this problem. They gave importance to G-mean. This performance measurement gives equal consideration to how well the model identifies injuries and non-injuries.

- ***Computational Demands vs Real-time Feasibility***:

Sophisticated architectures like DCAE-DNNs, although accurate, require considerable computational resources, which may hinder their deployment in live athletic settings (Ye et al., 2023; Yang et al., 2024).

- ***Model Interpretability***:

Deep learning models that use autoencoders and multilayer DNNs often lack transparency. Zhao and Li (2023) did not investigate interpretability methods. This restricts an understanding of the model's decision processes. Such limits hinder the widespread use of the models in clinical work besides sports medicine.

- ***Single Modality Focus**:*

  Many studies are based on motion sensor data alone. To include different types of data, for example, physiological signals, video capture along with contextual training data, can improve a model's dependability and predictive precision.

Medical Image-based inputs:

Latest Techniques

Deep learning application in medical imaging gave a better way to find and name sports injuries. Recent studies show diverse, focused models developed to make injury identification more correct through modern neural network designs.

Song et al. (2021) developed a deep convolutional neural network (CNN). It classifies musculoskeletal injuries using MRI scans. Model design was changed to get spatial features out of imaging data. To stop overfitting, since datasets are not big, data augmentation plans that use rotation, scaling along with flipping were used.

In a different study, Hatamzadeh et al. (2020) presented a hybrid CNN-LSTM network that detects anterior cruciate ligament (ACL) injuries. MRI slices went through a CNN for spatial feature extraction. An LSTM layer handled sequential information across slices. This treated data as time-series for improved injury pattern recognition.

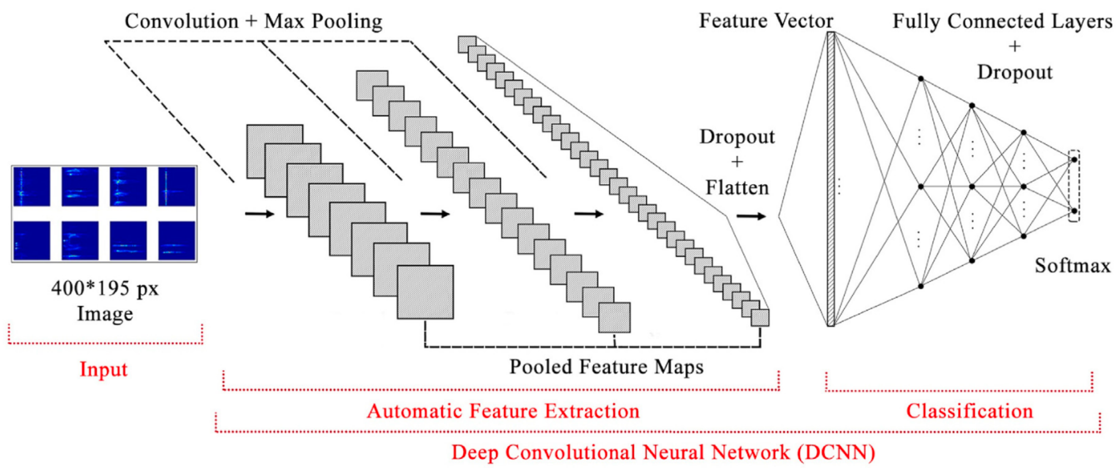

Figure 6 – Architecture of designed DCNN from (Research paper: A new method of diagnosing athlete's anterior cruciate ligament health status using surface electromyography and deep convolutional neural network by Hatamzadeh et al.)

Akhoondian (2025) suggested a Residual Attention U-Net (RAU-Net) for automatic segmentation of musculoskeletal injuries in MRI data. The architecture develops the standard U-Net. Residual connections and attention mechanisms help with more precise identification of injured regions inside anatomical structures.

Chen and Zhang (2022) created a convolutional neural network setup with various scales. It identifies small damages to skeletal muscles from ultrasound pictures. The design merged characteristics at several size levels. It captured detailed and general injury types. This improved the accuracy besides the correct identification of injuries. The prior investigations show an expanding pattern. There is a merge of spatial, sequential along with multi-scale data. This improves injury detection from medical images using deep learning.

Effectiveness of the Techniques

Models from the studies show performance gains compared to older diagnostic methods. Song et al. (2021) stated a 93.2 % classification accuracy on the test dataset. This is higher than older machine learning models that used features extraction. Hatamzadeh et al. (2020) got a 95.6 % accuracy for ACL injury detection with their CNN-LSTM hybrid. That highlights the benefit of combining spatial plus temporal learning. In 2025 Akhoondian showed that the RAU-Net architecture got a Dice coefficient of 0.881. This reflects good injury segmentation, important for diagnosis that is accurate. Nan Chen and Yang Zhang (2022) reached 92 % sensitivity and 89 % specificity in detecting minor muscle injuries. This indicates decent performance in balancing true positives and limiting false alarms. Combining attention modules, hybrid sequential models along with multi-scale feature fusion created a substantial increase in diagnostic performance across different imaging methods.

Challenges and Limitations

Despite encouraging results, the studies reviewed highlighted several important limitations:

- ***Small Dataset Sizes:***

  Song et al. (2021)and Hatamzadeh et al. (2020)worked with relatively few MRI samples, which risks limiting model generalization to broader populations.

- ***Labeling Inconsistencies:***

  Akhoondian (2025) noted variability in injury segmentation annotations across different radiologists, potentially affecting training data quality.

- ***High Computational Costs:***

  Models like RAU-Net and multi-scale CNNs introduced by Akhoondian (2025) and Chen and Zhang (2022)required extensive computational resources, complicating deployment for real-time clinical use.

- ***Interpretability Challenges:***

  Although attention mechanisms improved localization, fully understanding the model's decision-making process remained difficult, which could limit adoption in clinical settings (Nan Chen and Yang Zhang, 2022).

- ***Injury Class Imbalance:***

  The underrepresentation of minor injuries in datasets led to biases in model learning, skewing results toward more severe cases (Nan Chen and Yang Zhang, 2022).

In summary, while deep learning is revolutionizing injury detection from medical imaging, challenges related to data diversity, model interpretability, and computational efficiency need further research to facilitate real-world implementation.

Industry Applications of Deep Learning

Deep learning a type of machine learning, became a useful instrument in several areas. This is because of a notable capability to process involved data sets with many values. Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory models, Transformers along with Generative Adversarial Networks are designs it uses. Transportation as well as security sectors see significant development. The next sections examine how people use these models (Miotto et al., 2018; Ozcan et al., 2024; Rane et al., 2024). It describes how they affect the direction of the areas they apply to.

Deep Learning in Healthcare:

A significant employment of deep learning in healthcare is medical imaging analysis. Convolutional Neural Networks displayed abilities in the finding and sorting of conditions from various body part images. For example, Esteva et al. (2017) built a deep learning system. It could sort skin problems with an accuracy like certified skin doctors. This CNN received training using 129,450 clinic images showing 2,032 different sicknesses and worked at the same level as 21 skin doctors at tasks related to finding the most common cancers.

DeepMind's medical AI system showed the capability to detect over 50 eye sicknesses from optical coherence tomography scans with an accuracy near to that of expert eye doctors (De Fauw et al., 2018). It gave diagnoses and made treatment suggestions. This could decrease the time between sickness finding plus providing care for conditions threatening eyesight.

When there was the COVID-19 pandemic, deep learning use became faster for chest X-ray and CT scan examination. Wang et al. (2021) developed COVID-Net. This open-source deep neural network was made specifically for finding COVID-19 cases from chest X-rays. Their model obtained high sensitivity and specificity amounts, showing AI systems could serve as quick checking tools during public health emergencies.

Deep learning changed pharmaceutical research by speeding up drug finding processes that need years of lab experiments. Recurrent neural networks plus generative adversarial networks were used to predict molecular qualities, make new chemical structures and improve possible drug discovery outcomes.

AtomNet, made by Atomwise, provides an example of deep learning's use in drug discovery. The system utilizes convolutional neural networks to guess the bioactivity of tiny molecules and find compounds that could attach to target proteins. In one achievement, AtomNet found two compounds that showed promise against the Ebola virus (Wallach et al., 2015).

Zhavoronkov et al. (2019) showed how deep learning could greatly speed up drug development. They used generative tensorial reinforcement learning to discover potent DDR1 kinase inhibitors in just 21 days. The usual process needs years. The research team proved the approach by making and testing the AI-created molecules, confirming their potency plus selectivity.

Deep learning algorithms are employed to examine patient data and create treatment plans specific to each person. These systems combine various data types, like genetic information, electronic health records as well as habits, to predict how patients respond to various treatments.

One implementation comes from the Mayo Clinic. The clinic worked with Nference to create an AI system that examines unstructured clinical notes to find patterns and links that people might not notice. The system has been valuable in finding rare sickness presentations plus unexpected drug interactions (Murali et al., 2022).

Ardila et al. (2019) showed how deep learning could improve lung cancer prediction by examining low-dose chest computed tomography scans. Their model did better than radiologists when prior CT images did not exist. It showed similar performance when prior images were available, enabling earlier actions for this deadly sickness.

Deep Learning in Transportation

Autonomous Vehicles

Self-driving vehicles represent a good example of deep learning in transportation. These systems rely on deep neural networks. They handle data gathered from devices such as cameras, lidar along with radar. This handling lets them comprehend the surroundings and determine driving actions.

An early demonstration of deep learning used for automatic transportation came from Google's Self-Driving Car Project. Vehicles from that project used both CNNs and recurrent neural networks. Those networks identified objects, predicted their activity as well as made safe routes. Waymo's automatic taxis traveled more than 20 million miles on public streets. They did this across many cities in the United States. This demonstrates a tangible usage of the technology (Waymo, 2023).

NVIDIA's Bojarski et al. (2016) presented a full learning system for automatic driving. A CNN directly changed original pixels from a front-facing camera to steering commands. This avoided dividing the issue into detection, path planning next to control parts. It showed deep learning could simplify difficult engineering issues.

Traffic Management and Optimization

Deep learning affected traffic management systems and improved correctness in traffic prediction alongside methodology.

For example, Pittsburgh has Surtrac, a traffic signal control system. Surtrac employs reinforcement learning to improve traffic flow. The system decreased travel times by 25 % and wait times at intersections by 40 %. Emissions went down by 21 % (Smith et al., 2013).

Li et al. (2018) created a deep learning method. They utilized graph convolutional neural networks to forecast traffic flow. The method demonstrated better correctness compared to established processes. Considering space dependencies between road parts and time changes of traffic models, it revealed how neural networks can capture connections in transportation networks.

Public Transportation Optimization

Deep learning also helped public transportation systems. This involved demand prediction, route change along with maintenance preparation.

In London, Transport for London (TfL) created a deep learning system. The system reviews data from ticketing systems, vehicle sensors as well as weather details. It forecasts passenger needs across the system. This forecast helps TfL allocate resources effectively and respond to shifts (Transport for London, 2022).

Ni et al. (2020) demonstrated recurrent neural networks can predict bus arrival times. This approach had improved precision over older methods. The method employed past information, current location, weather next to occurrences. Prediction errors were under three minutes for most routes.

Deep Learning in Security

Deep learning changes video surveillance. It permits automated video supervision. This method detects unusual actions and points out persons of interest. It also spots atypical behaviors.

In Qatar, at Hamad International Airport, one sees a system with intelligent video analysis. This system uses deep learning to observe many video signals. It automatically identifies abandoned objects, unauthorized access to restricted areas along with hazardous crowd accumulation (Hamad International Airport, 2021).

Sultani et al. (2018) built a deep learning model. It functions to detect unusual activity in real-time within surveillance videos. The system once trained on a dataset with 13 unusual events like fights and thefts, had acceptable detection scores. It demonstrated a low number of incorrect alarms. This showed that deep learning functions for security monitoring.

Deep learning models also find use in cybersecurity. They discover malware, locate network intrusions as well as halt phishing attacks. This is done through analyzing patterns unseen by older systems.

One company in cybersecurity uses deep learning algorithms. This sets up a typical activity pattern for each user and device inside a business network. The method permits the system to find small changes that hint at a security issue. In an event that has been recorded, Darktrace's AI found and stopped a ransomware attack prior to file encryption. That action saved the company millions in potential losses (Darktrace, 2022).

Vinayakumar et al. (2019) displayed how deep learning raises malware detection numbers. Their way uses deep neural networks to examine executable file properties. It reached detection numbers higher than 98 % for previously unseen malware.

Because of deep learning biometric authentication saw changes, it improves facial recognition, fingerprint matching next to other biometric identification methods.

IDEMIA has a MorphoWave contactless fingerprint recognition product. It uses deep learning to handle fingerprints during a hand's movement over the sensor. Secure sites and airports around the globe employ this technology. It handles several thousand individuals each day with acceptable precision and minor errors (IDEMIA, 2023).

Schroff et al. (2015) created FaceNet, a deep learning system for facial recognition. It achieved acceptable precision on comparison datasets. The process changed facial images into a smaller representation. Measurements in this representation related to facial likeness. The process let programs perform face verification and grouping with precision.

Future Directions and Challenges

Deep learning produced change in healthcare, transportation along with security. New events show additional change is possible. Healthcare systems process data from many locations. Records as well as wearables present better patient views. Data protection clearance next to medical use makes problems.

Transportation moves to higher connection rates. Deep learning can assist self-driving vehicles, traffic direction next to public transport coordinate. Questions about ethics in emergencies and liability for AI errors are problems.

In security new attack types complicate deep learning. Models require regular updates to remain safe. Increased use of face and fingerprint scans produces privacy problems in addition to the problems require attention. Through all areas it is hard to know why deep learning systems selected certain outcomes. The need for easily understood models gets larger as machine decisions get heavier, particularly in high consequence areas.

Potential future solutions:

Deep learning advances along with its application to athlete injury prediction. Its potential for greater sophistication, precision along with clinical application is obvious. One path involves multimodal deep learning models. These models integrate different athlete data categories, like biomechanical data, physiological signals such as heart rate and EMG, video motion capture, GPS tracking as well as past injury records, inside one prediction system.

Current models frequently examine single data categories like sensor data or video analysis, but later systems must employ multiple data streams together. Research demonstrates that multimodal learning can locate complex relationships among physical, physiological and environmental factors that influence injury likelihood (Li et al., 2023).

Temporal deep learning models hold potential. Recurrent Neural Networks (RNNs), Long Short-Term Memory networks (LSTMs) as well as Transformer-based architectures model athlete data accumulated through time. Those models can track shifts to injury likelihood over time via analysis of training loads, fatigue measures and performance data sequences (Wang et al., 2022). For example, a Transformer model could assess an athlete's injury likelihood weeks ahead based on workload plus recovery alterations.

Self-supervised learning and few-shot learning methods seem to have a role. Labeled injury datasets contain few examples and are expensive to construct. Next models could train at first on large quantities of unlabeled biomechanical or physiological data, after that adapt with few labeled examples, decreasing data demands (Zhou et al., 2024).

A developing area contains explainable deep learning (XAI). Future systems will incorporate methods that both predict injury probability plus give the causes. They will display specific movement patterns, load data, or physiological changes that most cause an athlete's risk score. This explanation feature helps acceptance by coaches, physiotherapists and sports scientists. Those experts must have confidence in and then follow AI advice (Molnar et al., 2023).

Real-time uses should grow. Wearable devices carrying small deep learning models might soon predict injury probability during training. Coaches will obtain immediate warnings if an athlete exhibits indications of higher injury probability (Kim et al., 2022). Edge AI models created for low-power hardware will permit this even in very active sports environments.

The future for deep learning in athlete injury prediction progresses toward unified, real-time, explainable systems that require little supervision. These will offer individualized, proactive injury management programs.

Current Limitations in my research area:

Deep learning models appear hopeful, but some limits now hinder their power to predict athlete injuries. Data is scarce plus data sets are unequal. Securing good data about athlete injuries is hard. This comes from privacy matters, small team numbers along with fewer injury cases than normal practice. Models then overfit and generalize badly to new athletes or sports (Dijkstra et al., 2021). Injury data often is unequal. Samples that do not show injury are much bigger than injury cases. Models then falsely predict that no injury happens.

Data source changes complicate items. Systems that watch athletes change between teams and sports. Sensor types sampling rates as well as recording strategies are different. This change makes it hard to build general models that do well across sports groups unless they are retrained much (Claudino et al., 2019).

Time presents a complicated picture. Injuries frequently come from stress accumulation. Deep learning methods now treat athlete data as single cases instead of sequences in progression. When time-based modeling is absent, early signs of injury accumulation pass unnoticed.

The unclear nature of deep learning hinders practical use. Trainers plus medical staff are slow to trust AI predictions they cannot explain. This is true especially for decisions about athlete health and protection (Samek et al., 2020). Implementation questions show up. To run deep learning models in real time on portable gear (like wearables) is tough. This is from hardware limits; battery drain next to fast inference during sports.

Potential Solutions:

Possible paths to take, plus technical plans, can handle current problems with deep learning use in injury forecasts.

Data Augmentation and Synthetic Data Generation

One can apply data augmentation. Another is synthetic oversampling with SMOTE. A third selection, GAN-based production of made-up injury examples, could help balance datasets. This can lower data scarcity. (Chawla et al., 2022).

Transfer Learning and Domain Adaptation

From using models prepared in advance on extensive, similar datasets plus then tuning them for certain sports or teams, transfer learning can lessen the reliance on huge, labeled datasets. It also betters generalization across different groups. (Tan et al., 2021).

Temporal Sequence Modeling

The upcoming work should focus on BiLSTM, GRU along with Transformer models. These find time-series trends in workload, biomechanics as well as physiology, providing a more precise look at injury risk buildup. (Wang et al., 2022).

Explainable AI (XAI) Techniques

Adding methods like Layer-wise Relevance Propagation (LRP), SHAP values, or saliency maps into deep learning models makes forecasts understandable. This creates more belief among those who use them. (Molnar et al., 2023).

Edge Computing and Model Compression

Such as model pruning, quantization next to knowledge distillation, permit the placement of deep learning models on wearable items. This permits injury risk tracking in real time during exercises and contests. (Kim et al., 2022).

Federated Learning for Privacy-Preserving Injury Prediction

Instead of putting delicate athlete information in a central spot, federated learning permits models to be trained across many locations. Here, the data is kept close by. This plan could unlock bigger, more varied datasets without risking athlete privacy. (Li et al., 2023).

Conclusion

This thorough examination uncovered the potential of deep neural networks for large changes in athlete injury prediction plus prevention. An analysis of different DNN structures, from CNNs and RNNs to combined designs with LSTM networks besides autoencoders, displayed progress in both correctness and usefulness across different sports. The material presents two primary methods: wearable technology systems which utilize motion data for current monitoring along with medical imaging methods which improve injury diagnosis via detailed pattern identification. Both methods demonstrated clear gains compared to former methods, with several models getting prediction correctness above 90 %, mainly in areas such as ACL injury diagnosis also movement pattern study. In spite of the favorable outcomes, challenges remain. A shortage of data and data imbalance are obstacles, with injury datasets generally showing a greater number of non-injury examples than injury examples. This imbalance together with changes in data collection processes across different sports plus teams, complicates the creation of general models. The opaque quality of deep learning systems prevents widespread use among sports medicine experts who demand clear decision processes. Later progress in this area shows potential to address limits via a few original methods. Multimodal deep learning structures which join biomechanical, physiological as well as contextual data propose more complete injury risk evaluations. Complex temporal modeling methods, including transformers and bidirectional LSTMs, could better capture the ongoing development of injuries. The addition of explainable AI methods will probably improve model clarity besides build greater confidence among experts. With edge computing improvements that permit the use of complex models directly on wearable devices next to as federated learning methods address privacy problems connected to sensitive athlete data; one can expect increasingly personalized, current injury prediction systems. These improvements, with transfer learning and artificial data generation to defeat data limits, point to a future where early injury handling becomes a standard method across all sport tiers. Deep learning also sports medicine coming together represents a basic change in method, from fixing injuries to early prevention. This change should improve how long athletes perform, how well they do in addition to how they feel. As these technologies grow and find greater acceptance, they potentially reduce injury rates plus transform sports medicine methods globally.

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