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Article

Research on injury prevention strategies of biomechanical analysis in physical education teaching

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Abstract: Physical education instruction has several issues on injuries as a result of interruptions to the learning, participation, or physical activity of the students. Existing strategies concern the risk prevention and warm-up activities without addressing personal characteristics and anatomical and kinematic prerequisites that underlie the occurrence of injury. The biomechanical evaluation of human motion can determine factors such as joint stresses, muscle loads, and motion patterns. This proceeding strives at eradicating the aspects of biomechanics in expanding the protective measures of injury prevention in physical education teaching. Beside the motion capture system, the force plate measurement and the electromyography (EMG) data movement patterns and joint load are measured biomechanically as accurately as possible. The accumulative data have to pass through cleaning and standardization steps to provide a certain level of reliability. In this case, the use of Fast Fourier Transform (FFT) extracts features of the movements relating to the frequency domain to undergo further analysis. Subsequently, an efficient Earthworm Optimized Graph Neural network (EEO-GNN) is employed to identify injury risk elements through modeling complex biomechanical relationships and patterns. The EEO-GNN model efficiently predicted ability injury hotspots by analyzing joint stresses, muscle activation, and motion irregularities. It is surpassing previous approaches in terms of F1-score (96.2%), recall (95.2%), accuracy (96%), and precision (95%). It underscores the ability to integrate superior biomechanical analysis and deep learning procedures to enhance injury prevention, enhance motion mechanics, and foster safer and greater effective physical education environments.

Keywords: injury; prevention strategies; biomechanic; physical education; efficient earthworm optimized graph neural network (EEO-GNN)

1. Introduction

Injury prevention is one of the most critical aspects of teaching in physical education, as it ensures that students taking part in physical activities remain safe and sound (Evans and Sims, 2022). The inclusion of biomechanical analysis can help to reduce the occurrence of injuries. Biomechanics is the science of bodily movement; it examines body motions, joint angles, muscle forces, and overall posture (Zhao, 2024). It analyzes the risk variables that contribute to injuries and assists in the development of prevention methods. The biomechanical analysis enables the educator to perceive and correct the technique of the students during the activities (Prieto-González et al., 2021). It can be through motion capture technology, video analysis, or wearable sensors that track the body movement. From the assessment of the movements, a PE teacher is also able to identify faulty posture, poor alignment, or inefficient mechanics that could predispose students to overuse injuries, strains, or sprains (Bonilla et al., 2022). This proactive approach not only focuses on immediate injury prevention but also emphasizes the importance of developing a long-term understanding of body mechanics among students. By fostering this awareness, educators can instill a sense of responsibility in students for their own physical health. Furthermore, biomechanics can be integrated into various sports and physical activities, allowing for a more comprehensive understanding of how different movements affect the body. This holistic view encourages students to be more mindful of their actions, ultimately leading to safer participation in sports and recreational activities.

Furthermore, biomechanical concepts can be used to help build tailored injury prevention measures. For example, teaching students adequate warm-up and cool-down procedures, as well as stretching exercises based on biomechanical principles, can assist them in improving flexibility, increasing joint mobility, and reducing muscle injuries (Prentice et al., 2024). Incorporating these practices into the curriculum not only enhances students' physical capabilities but also promotes a culture of safety and awareness in physical education. By emphasizing the importance of these routines, teachers can help students understand the critical role that proper preparation plays in preventing injuries. This understanding can lead to lifelong habits that prioritize safety and well-being, extending beyond the classroom and into their daily lives. Biomechanics can be used to create appropriate equipment and footwear, as well as to modify training or sports techniques to better suit an individual's physical ability. The customization of equipment, such as shoes designed to provide better support or protection based on an individual's biomechanics, can significantly reduce the risk of injuries. Additionally, adapting training techniques to fit each student's unique physical characteristics allows for a more personalized approach to physical education, ensuring that all students can participate safely and effectively. This individualized attention not only benefits injury prevention but also enhances overall performance and enjoyment of physical activities.

A closer incorporation of biomechanical evaluation in the instructions of physical education makes the environment more productive and safer (Shan, 2023). This integration fosters an atmosphere where students feel supported and encouraged to explore their physical capabilities without the fear of injury. By creating such an environment, educators can motivate students to engage more fully in physical activities, which is essential for their overall development and well-being. Moreover, a focus on safety and injury prevention can lead to increased participation rates in physical education programs, as students recognize the value of these practices. It also improves the physical strength of the students and reduces cases of physical injuries that can occur. Also, advances in technology, which include providing feedback in real-time and using wearables, have made its application in physical education easy through biomechanics as coaches and teachers are able to develop and implement injury prevention measures in relation to every learner (Rebelo et al., 2023). This improves the standard of physical education while also bolstering kids' future physical fitness and health (Garcia et al., 2023). Nevertheless, the cost and accessibility of quality technology offer a challenge to the use of biomechanical analysis in physical education. Also, due to biomechanical data analysis, the need to interpret data with specific and specialized knowledge is needed, and such knowledge may not be available with the teachers or educators. Due to time, different assessment activities cannot be incorporated into the lesson due to a lack of enough time. However, this can present challenges in minimizing the differences among students while trying to come up with prevention measures that can be implemented across the entire population.

Contribution and objective

This investigates how crucial biomechanical assessment is to preventing injuries in physical education. By examining joint stresses, muscle loads, and motion patterns, it employs an EEO-GNN model to pinpoint injury risk factors. The model's ability to identify injury hotspots emphasizes how combining deep learning and biomechanical analysis can enhance motion mechanics, reduce injuries, and provide safer physical education settings.

- Biomechanical data, including joint angles, muscle activation, and ground reaction forces, are collected by motion capture systems, force plates, and EMG sensors while students are performing several physical activities.
- Cleaned raw data, normalized to be consistent, and further segmented to ensure reliable feature extraction in improving the accuracy of injury risk prediction and biomechanical assessment.
- FFT is applied to the time-domain motion signals for the generation of frequency-domain representations, which accentuate biomechanical movement patterns, joint stress fluctuations, and muscle activation frequencies for effective injury risk assessment.
- EEO-GNN is a biomechanical modeling that optimizes graphical structures to spatially capture the temporal patterns, hence potential injury hotspots with deep-learning-driven biomechanical insights.

The remaining parts of the research are as follows: Part 2 includes a literature review; Part 3 explains the suggested approach; Part 4 outcomes and discussion; and Part 5 concludes the evaluation of findings.

2. Literature review

The prevention of injuries improved in physical education employing real-time tracking and deep learning by Leilei et al. (2021). It analyzed student mobility using the Theory of Humanities Education (ToHE) and utilized the Global Positioning System (GPS) for emergency responses. The device detects injuries with an accuracy of 90%. Limitations included potential GPS errors and the necessity for further validation in a variety of circumstances.

Cui et al. (2022) investigated physical rehabilitation and injury prevention in physical education using wearable technology. It gathered and analyzed workout data in real-time, including heart rate and steps and used machine learning and the Internet of Things. The results, injury risk prediction, and preventative advice were helpful. Variability in individual reactions to training and problems with data accuracy were limited. Mishra et al. (2025) used an AI-driven framework to examine how physical education instruction affects injury prevention. It gathers movement data from players, uses AI to detect injuries, and gives coaches and medical experts insights. The findings emphasized AI's function in proactive sports administration. Data variability and the requirement for customized models were among the drawbacks. Utilizing computer vision and long short-term memory networks, Ouf et al. (2024) aim to improve injury prevention by precisely monitoring push-up form. Finding the right and wrong methods was made possible by a well-selected dataset, which offered customized feedback. The training and testing F1 scores for the model were 0.9 and 0.85, respectively. One drawback was that it emphasizes push-ups, which calls for modification for more general sports use.

Xu and Tang (2021) apply machine learning technology to robot path planning for the purpose of minimizing basketball training-related injuries. The robot operated by using an advanced *Q*-Learning algorithm controlled by a fuzzy controller for obstacle avoidance when moving. The simulation showed that the algorithms performed path identification tasks quickly besides creating well-optimized paths. The system requires additional research to establish its practical usability and expandability in actual settings. Li et al. (2025) presented artificial intelligence and infrared thermal imaging as methods to enhance injury prevention in risky activities, specifically aerobics. The system acquired thermal images through multiple image enhancement approaches followed by deep learning processes to locate risky and tired zones. The results showed improved accuracy, while the assessment measurements could be negatively affected by both data validation concerns and external conditions.

Yang et al. (2024) were to enhance sports injury prevention by combining a back-propagation neural network (BPNN) model with wearable technologies to identify accurate sports actions. The approach used BPNN classifiers to extract and classify features, and it has been tested on running, and static activities. The findings revealed that 11 hidden layer nodes provided excellent recognition for running activities. It focuses on wearable system layers and recommends ways to prevent damage. The classifier performance for static activities was comparable. Xie et al. (2021) were to use machine learning to create an intelligent badminton training robot (IBTR) that can reduce player injuries. A Hidden Markov Model (HMM) was used by the system to assess the motions of athletes. The results indicate a recognition accuracy of 96.03% with improved HMM and 94.5% for robot interaction, indicating stability throughout 120 training sets. Limitations include challenges with different data set sizes.

3. Methodology

Biomechanical analyses of injury prevention in physical education were used by motion capture in force plates and EMG data. Preprocessing includes cleaning and standardization to ensure reliability. FFT is used to extract frequency-domain movement features. The models of biomechanical relations are performed by the EEO-GNN, which identifies risks of injury through joint stress, muscle activation, and movement irregularities. **Figure 1** shows the proposed research basic concept flow.

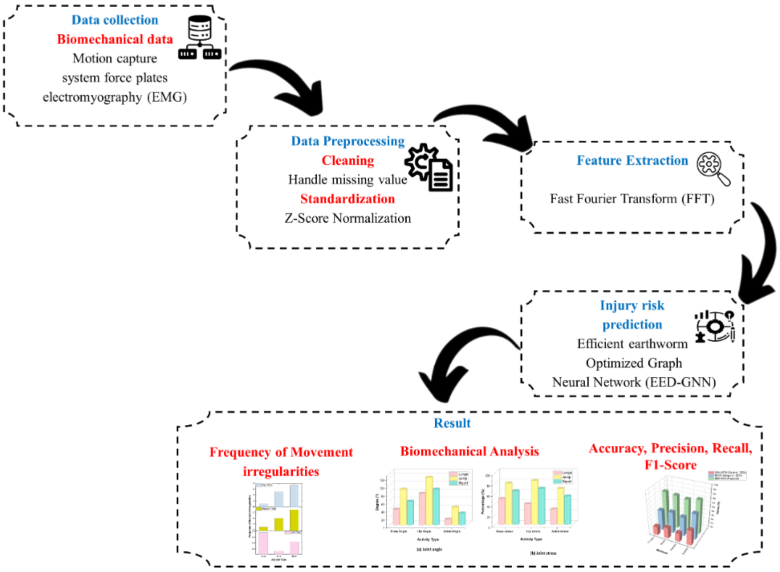

Figure 1. Basic concept of overall proposed research.

3.1. Data set

The biomechanical analysis utilized to prevent injuries in physical education was the primary focus of this dataset. It contains data concerning 1000 individuals, including biomechanical forces, joint angles, muscle activation (EMG), movement patterns, and injury risk variables. By investigating how individual movement mechanics can affect injury risk during physical activities, the dataset seeks to support the development of injury prevention techniques. The data is available on the Kaggle website: https://www.kaggle.com/datasets/ziya07/biomechanical-analysis-for-injury-prevention/data.

3.2. Data pre-processing

Preprocessing includes data cleaning and standardization of biomechanical data coming from motion capture systems, force plates, and EMG in the analysis of movement patterns and risk of injuries to ensure such data possesses consistency and reliability.

3.2.1. Handle missing data by MICE multiple imputation

Missing data is a very critical problem in the pre-processing phase, which is very important in applying deep learning models for injury prediction based on biomechanical analysis. In the real world, biomechanical data sets can have missing values resulting from any of the following: equipment fault, human error, or unavailability. Such anomalies, outlier joint angles, or unusual muscle activation patterns could also induce missing or wrong data points, which can be compensated for by the application of adequate repairing mechanisms. The use of MICE remains valuable when it comes to preventing injuries in biomechanical educational research for physical education students. The MICE algorithm takes care of missing data about student health and movement patterns and physical performance, which maintains the robustness and fairness of the dataset. The method generates various alternative datasets through imputation, allowing researchers to execute precise biomechanical injury examinations. The application of MICE techniques to this research improves injury prevention strategies by using complete data that helps decision-makers select appropriate physical education curriculum methods.

- Unimportant: Less than one percent of missing data can be handled by MICE multiple imputation.
- Manageable: One to five percent of the data are missing; standard imputation methods, such as MICE multiple imputation, can be used.
- Advanced: Missing data of more than five to fifteen percent may need some advanced procedures to maintain the data integrity, which includes MICE multiple imputation.
- Extreme: More than fifteen percent of data is missing; hence, data recovery is harder. It can be necessary to strongly consider whether the dataset can still be used or if it has to be re-collected.

3.2.2. *Z*-score normalization

The standardized method is commonly used to overcome issues with outliers and to standardize features in biomechanical data in the prediction of injury risk. In this respect, the technique ensures that all biomechanical features—joint angles, muscle activations, and force measurements—are transformed onto a common scale, allowing for a more accurate analysis of movement patterns and injury risks. In particular, each biomechanical feature's values are converted to normalized values using Equation (1) as follows:

$$x' = \frac{x - \mu}{\sigma} \tag{1}$$

where x is the raw value of the biomechanical feature, μ is the mean of that feature across all data points, and σ is the mean error of the feature. Biomechanical values under the mean are mapped to negative numbers after applying the *Z*-score normalization; those above the mean are represented by positive numbers, and finally, values amounting to exactly the mean get mapped to zero. This kind of transformation helps in determining important deviations from normal movement patterns that could predict injury risk.

3.3. Fast fourier transform (FFT) used for feature extraction

Biomechanical movements can be analyzed in the frequency domain by extracting the features of a signal through the Fast Fourier Transform. To convert time-domain data into their corresponding frequency components, such as joint angles, muscle activations, and ground response forces, this approach employs FFT. The latter represents a sum of sinusoidal constituents with different frequencies and amplitudes that sum up to create the original signal. FFT is an efficient algorithm in computing discrete FT, Equation (2) defined as follows.

$$W_l = \sum_{m=0}^{m=1} w_m f^{-\frac{j2\pi km}{M}}, l = 0, \dots l - 1 \tag{2}$$

In this Equation (2), w_m denotes the time collection input, W_l represents the domain of frequency output, and M is the wide variety of samples. By analyzing those frequency features, the individual wants to understand the movement patterns that could contribute to injury throughout physical activities.

3.4. EEO-GNN for injury risk prediction in physical education

An EEO-GNN model is proposed for the complicated biomechanical relation and predicting feasible injury areas in physical activities. EEO-GNN can capture problematic interdependencies among distinct biomechanical factors, inclusive of joint stresses, muscle activation, and irregular movement. The EEO algorithm also enhances the efficiency of the formula underlying the model for optimizing its parameters for optimal prediction of the concept's value. This can enable the EEO-GNN to recognize biomechanical data, estimate risk of injury factors, and gain much informative measures about increasing individualized preventative measures with physical education teaching.

3.4.1. Graph neural network (GNN)

The analyzing biomechanics in physical education, particularly in the aspect of prevention of injuries, it can be potentially useful to use GNN for the analysis and modeling of multiple interrelated factors that are biomechanical features. The square node could be "joint stresses" or "muscle activation levels" or could be "movement patterns"; these relate to each other like edges. The general objective is to understand how the different biomechanical variables, joint forces, and muscle activation rates. The general purpose is to determine how specifically joint forces and muscle activation of the GNN model can detect candidates for injury, patterns, and irregularities in movement data using information accumulation and propagation in neighboring nodes of related biomechanical data. The structure can follow Equation (3).

$$n_x^y = \emptyset\left(w_y^{k-1}, w_x^{k-1}\right) \quad \forall x \in M\,(y) \tag{3}$$

Here $M\,(y)$ denotes the set of neighboring nodes of node v, and w_y^{k-1} and w_x^{k-1} represent features of nodes y and x, respectively, in layer $k-1$. The function $\emptyset(\cdot)$ defines how information (messages) is propagated between nodes.

$$w_y^k = \Psi\left(w_y^{k-1}, \rho\left(\left\{n_x^y : x \in M(y)\right\}\right)\right) \tag{4}$$

Here, in Equation (4), $\rho(\cdot)$ is the aggregation function that aggregates messages from neighboring nodes, and $\psi(\cdot)$ updates the features of node y based on its previous features and the aggregated messages. It is important to emphasize the interaction of biomechanical features and how those interactions can help in identifying injury risks. The aim is to use GNN in learning, understanding, and predicting injury-prone movement with regard to joint stresses and muscle loads, based on other biomechanical parameters and their interactions.

3.4.2. Efficient earthworm optimized (EEO)

The optimization is realized by the EEO algorithm to enhance the performance of the GNN. Model parameters are fine-tuned by EEO in terms of an efficient search for the best configuration, aiming at better injury risk prediction accuracy. The EEO is developed by combining the Earthworm Optimization (EWO) algorithm and the Elite Oppositional-Based Learning (EOBL) strategy. The EOBL strategy enriches the optimization techniques' search diversity and hence provides solid and better solutions. In biomechanical injury prediction, EOBL can be applied to enhance movement pattern analysis by improving joint stress and muscle activation analysis. With elite solutions, EOBL improves initialization and increases the likelihood of discovering optimal biomechanical risk factors. An elite opposition solution is defined by the EOBL mechanism for each candidate solution based on the fittest movement pattern representation. The Equation (5) is as follows:

$$\widetilde{w}_{ij} = l(ka_j + va_j) - w_{fi} \tag{5}$$

where $i = 1,2,3,\dots,\mathrm{dim}$ denotes biomechanical parameters like joint angles and force outputs; $j = 1,2,3,\dots,n$ denotes individual movement samples; l is a random value between [0, 1]; ka_j and va_j represent the lower and upper boundaries of biomechanical constraints; w_{fi} is the elite biomechanical pattern derived from observed data. Additional hard constraints are added to ensure the generated solutions remain within physiologically valid ranges as defined in Equations (6) and (7).

$$ka_j = \min(w_{j,i}) \tag{6}$$

$$va_i = \max(w_{j,i}) \tag{7}$$

If the calculated $w_{j,i}$ exceeds biomechanical feasible restrictions, it is defined as follows in Equation (8):

$$\widetilde{w}_{j,i} \ = \ \text{rand}\ (ka_i, va_i)\ \left[\text{if}\ \widetilde{w}_{i,j} < w_{\min}\ \text{OR}\ w_{j,i} > w_{\max}\right] \tag{8}$$

where $w_{\min}$ and $x_{\max}$ represent the physiological moving range. The EEO algorithm efficiently refines biomechanical risk factor identification by embedding EOBL in the initialization stage to give rise to improved injury prevention strategies with physical education.

The proposed EEO-GNN method models the complex biomechanical relations to predict the risk of injury in physical education through the analysis of joint stresses, muscle activation, and movement patterns. The EEO algorithm optimizes the parameters of GNN to improve prediction accuracy, developing personalized injury prevention strategies with advanced biomechanical data analysis. Algorithm 1 shows the EEO-GNN.

The EEO serves as an optimization method for GNN development to enhance injury risk forecast accuracy when processing biomechanical data. The approach optimizes GNN parameters through a method that enhances its ability to analyze and predict injury risks. Evaluation metrics for model performance include accuracy alongside precision, recall, and F1-score used to guarantee effectiveness in biomechanical analysis. The efficacy of the EEO algorithm in GNN parameter optimization is demonstrated by the optimization convergence in the parameter search procedure. The convergence curves give a direct assessment of the algorithm's mathematical performance and target function optimization rate by showing how it gets closer to its ideal answer. With this update, it can learn more about stability variables and final results over the course of optimization. As long as the results showed exceptional efficacy, these technical details are valuable when assessing how well the EEO algorithm improved model performance.

Algorithm 1 EEO-GNN

```
import tensorflow as tf
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from EEO_algorithm import EEO_optimizer
from GNN_model import GNN
# Hyperparameters
EEO_hyperparameters =
 {'population_size': 50, 'iteration_count': 1000, 'learning_rate': 0.001, 'elite_fraction': 0.2,
     'biomechanical_constraints': {'knee': (0, 180), 'hip': (0, 180), 'ankle': (0, 180)}}
# Build and Optimize GNN
def build_optimized_GNN(data, labels):
 model = GNN(data.shape[1:])
 model.compile(optimizer = 'adam', loss = 'binary_crossentropy', metrics = ['accuracy'])
 model.set_weights(EEO_optimizer.optimize(model, data, labels,** EEO_hyperparameters))
 return model
# Evaluate Model
def evaluate_model(model, test_data, test_labels):
 preds = model.predict(test_data)
 metrics = [accuracy_score, precision_score, recall_score, f1_score]
 print({metric.__name__: metric(test_labels, preds) for metric in metrics})
# Main
def main(dataset, labels):
 model = build_optimized_GNN(dataset, labels)
 evaluate_model(model,* get_test_data())
# Run
dataset = load_dataset()
labels = load_labels()
main(dataset, labels)
```

4. Result and discussion

Extensive biomechanical data analysis in this experiment shows how well the Efficient Earthworm Optimized Graph Neural Network (EEO-GNN) functions in risk region prediction. A computer system with Windows 10-controlled operation used an Intel i7 CPU core accompanied by 64 GB memory, a 256 GB storage drive, a 1070 GPU, and Python 3.6.3 as its programming language.

The GNN nodes include essential biomechanical elements that combine joint stress with muscle activation and movement irregularities, and the edges indicate how these elements relate to each other. Each stress node related to joints receives connections from nodes depicting muscle activations, thereby demonstrating how force from muscles affects joint loads. A connection exists between muscle activation nodes and movement irregularity nodes to demonstrate how irregular movements cause increased stress. The EEO-GNN model uses its learned knowledge of complicated system dynamics to locate potential injury areas for improved preventive measures through biomechanical movement behavioral analysis. **Figure 2** presents the feature correlation heat map.

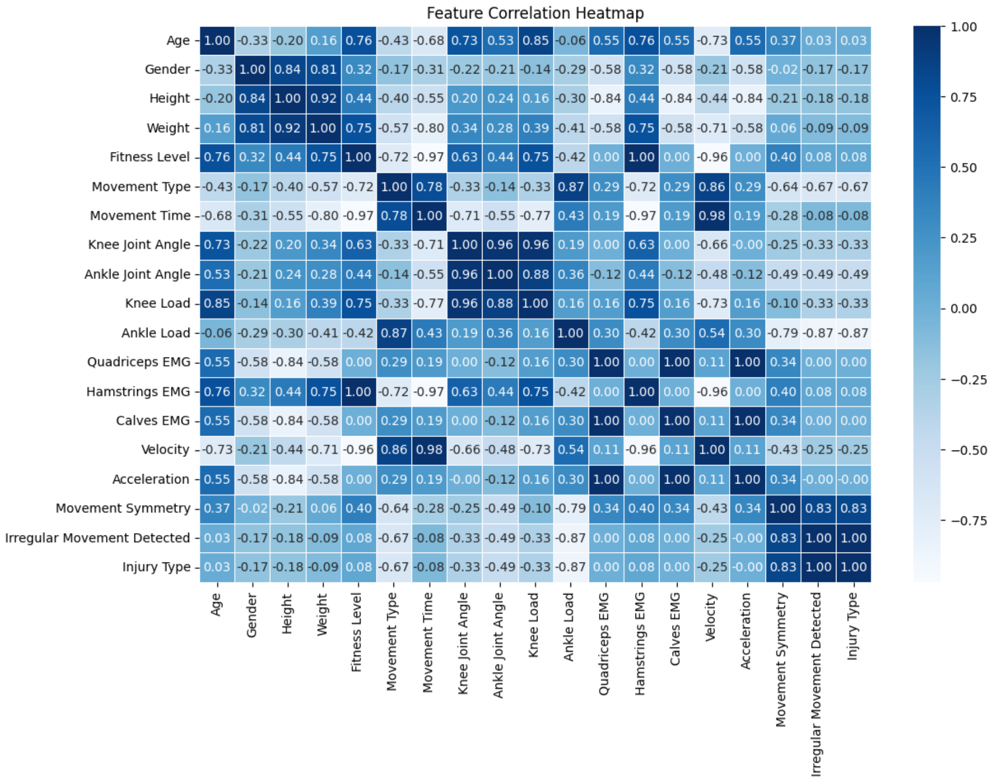

Figure 2. Graphical representation of feature correlation heat map.

The EEO-GNN system identified abnormally patterned movements for lunge, jump, and squat movements. The proposed system also measures irregular activities in regard to three risk levels: low, medium, and high, implemented with biomechanics data as shown in **Figure 3**. The proposed system performs joint angle and stress measurements by biomechanical structural analysis to perform the above assessments as shown in **Figure 4 a,b**. The method identifies hot spots that are the areas under maximum stress: they are knee, hip, and ankle joints because these areas are under high risk of incurring an injury in movement patterns. The indicated procedure of risk assessment offers clear guidelines on how to measure injury risks of different movements while exercising. Providing information that can help prevent or minimize injuries and improve performance in areas related to physical training represents the aim.

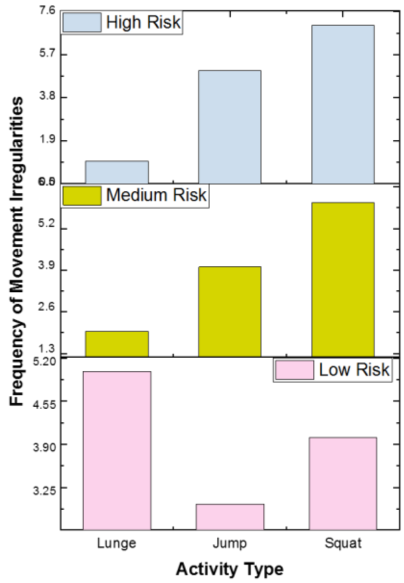

Figure 3. Frequency analysis of irregular movements.

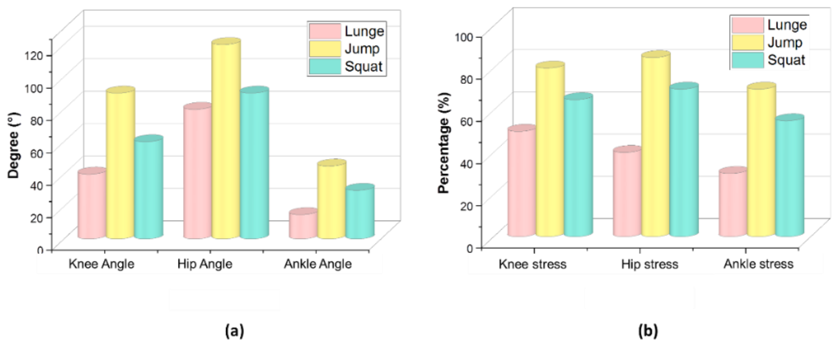

Figure 4. Biomechanical assessment of: **(a)** joint angle; **(b)** joint stress.

The proposed EEO-GNN model achieves exceptional results in injury prediction according to its ROC-AUC curve analysis shown in **Figure 5**. The model shows outstanding identification potential for injury risk factors because its AUC value reaches 0.97, demonstrating superior precision in positive and negative prediction zones for physical education injury prevention.

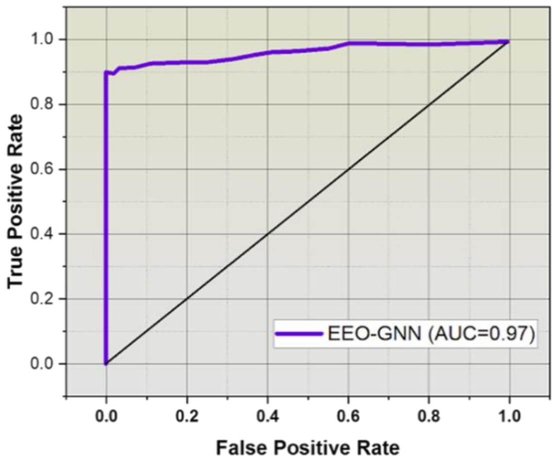

Figure 5. ROC-AUC curve for the EEO-GNN model in injury prediction.

4.1. Experimental metrics

The EEO-GNN-based injury prevention model utilizes four essential experimental metrics, including accuracy, precision, recall, and F1-score for validation purposes. The proposed EEO-GNN is compared with more traditional models for injury prediction, including the CNN-LSTM (Cai et al., 2024) and the RCNN (Wang et al., 2024), to which biomechanical analysis of injury risk prediction.

Accuracy is used to determine the level of precision in the prediction model. It can be computed as the number of correct classifications of all the test instances, including both true positives and true negatives. The accuracy of the EEO-GNN is expressed as 96%, which denotes 96% correctness in the positive or negative of the places it predicts. This is significantly higher in comparison with 87% of CNN-LSTM and 92% of RCNN.

Precision measures the amount of accurate positive outcomes among all the cases the model classified as positive. It defines the card's performance in the avoidance of false positive results. For instance, the results obtained proposed EEO-GNN has a precision of 95%, which means its results regarding a particular risk or abnormality can be considered correct in comparison with the CNN-LSTM model with 84% and the RCNN model with 89%.

Recall measures the number of actual positives that have been correctly classified by the model. It is defined as the ratio of the number of people who tested positive for the actual illness out of all those who were diagnosed to be positive by the test and on the actual disease. The EEO-GNN gives an impressive result in its recall of about 95.6%, which means that it has a high capability to capture almost all possible risks related to injuries compared to CNN LSTM at 85% and RCNN at 90%.

The F1 Score, which is the harmonious average of recall and accuracy, is particularly appropriate for instances when incorrect positives and false negatives could prove significant. Specifically, the F1-score for EEO-GNN is 96.2, and it shows that this method can be considered quite balanced and robust because, compared to the CNN-LSTM model, which was 84%, and the RCNN, which was 89.5%.

The overall trend from **Figure 6** and **Table 1** illustrates the proposed EEO-GNN method outperforms the existing CNN-LSTM and RCNN models for each of the performance measures. This superior performance underscores the enhanced ability of EEO-GNN to accurately detect biomechanical abnormalities and predict injury risks by reducing misclassifications.

Table 1. Comparison of injury risk prediction performance metrics.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
CNN-LSTM (Cai et al., 2024)	87	84	85	84
RCNN (Wang et al., 2024)	92	89	90	89.5
EEO-GNN (Proposed)	96	95	95.6	96.2

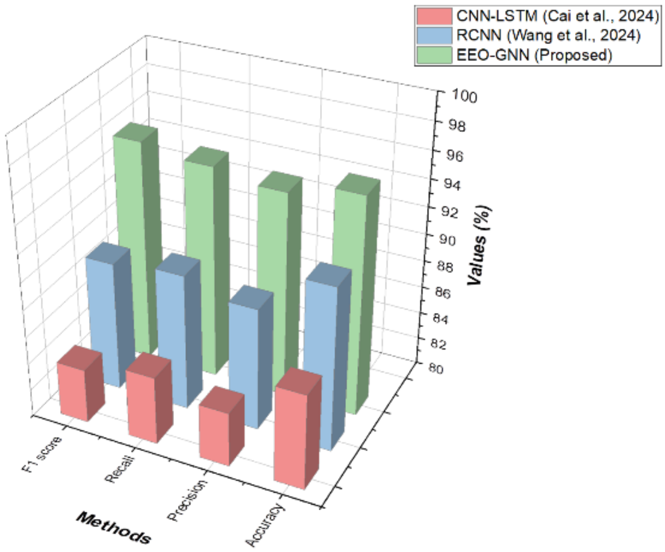

Figure 6. Evaluation of different injury risk prediction methods comparison.

4.2. Discussion

The analysis tools applied in PE instruction help identify inefficient movements from students while detecting potential risks so coaches can establish specific protective strategies. Teachers can maximize performance while minimizing injury risks through proper practices of posture along with proper technique and distribution of loads. The injury prevention approaches involving CNN-LSTM together with RCNN currently used for biomechanical analysis in physical education (PE) teaching show major operational limitations. The CNN-LSTM (Cai et al., 2024) shows limited effectiveness for monitoring continuous relationships between movement sequence information because its detection capabilities for precise biomechanical changes are limited. The processing speed of the RCNN method described by Wang et al. (2024) makes it inadequate for real-time usage by requiring lengthy computation and handling complicated spatial patterns. The currently available methods show restricted utility in developing customized injury prevention approaches because they do not work well with different physical activities and unique individual movement patterns.

The proposed EEO-GNN effectively deals with the limitations of traditional methods when it comes to capturing spatial-temporal correlations and long-term dependencies in biomechanical data. An optimized version of real-time injury risk prediction becomes achievable as it streamlines computational processing. The EEO-GNN model possesses properties adaptable to multiple physical activities during teaching physical education so it can deliver specific and precise injury prevention methodologies.

5. Conclusion

The research aims to establish the place and operational role of biomechanical analysis when developing injury prevention programs for physical education instruction. An efficient EEO-GNN model performed the identification of injury risk factors by constructing complex biomechanical relationships and movement patterns. To precisely determine joint loads, muscle activation, and movement irregularities, biomechanical data is gathered utilizing motion capture appliances, force plates, and EMG. Preprocessing was performed on the collected data, including cleaning and standardization, to enhance reliability and consistency. Feature extraction was performed using the FFT to analyze frequency-domain characteristics of movements. The EEO-GNN model effectively predicted possible injury hotspots by evaluating biomechanical stress factors, therefore bringing valuable insight into injury prevention. Experimental results proved better F1-score (96.2%), recall (95.2%), accuracy (96%), and precision (95%) of the proposed EEO-GNN method compared to the traditional approaches. The results underline the possibility of integration between advanced biomechanical analysis and deep-learning techniques in optimizing movement mechanics to decrease risks and provide safer, more effective physical education environments.

Limitation and future scope

Biomechanical analysis in physical education helps to prevent injuries by optimizing movement patterns and thus reducing strain. However, limitations include high equipment costs, technical complexity, and individual variability in response. In the future, advanced machine learning motion analysis, wearable technology for real-time feedback, personalized biomechanical assessment in injury prevention, and overall better performance of students in physical education can be envisioned.

Conflict of interest: The author declares no conflict of interest.

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