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Article

Wearable device data-driven athlete injury detection and rehabilitation monitoring algorithm

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Abstract: In recent years, sports wearable technology has completely changed the way athletes prepare, compete, and recover. Wearable technology has a lot to offer in the rehabilitation process, which is essential to an athlete's return to their best performance. Wearable devices for athlete injury detection pose potential challenges like data quality, security, and privacy, impacting accuracy, reliability, and effectiveness. To solve these problems, an innovative injury detection and rehabilitation monitoring (IDRM) system was proposed for athletes. By employing an adjustable recurrent neural network (ARNN) to detect anomalies in injury risks such as abnormal joint movements in athletes. In this study, biomechanics data was collected from sports athletes through wearable devices, and the wearable system provided feedback to the user. A redefined convolutional neural network (RCNN) was utilized to monitor the rehabilitation process. This system tracks athlete's rehabilitation progress and ensures that progress monitors were performed correctly, and the system, feasibility was evaluated on 10 healthy subjects performing 4 different rehabilitation exercises. Each exercise was performed four times monitoring and validation. The data was preprocessed using a Gaussian filter to remove noise from the obtained data. Then the features are extracted using independent component analysis (ICA) for dimensionality reduction from preprocessed data. The proposed method is implemented using Python software. In comparative analysis, the performance of ARNN showed high performance, with an F1-measure of 91.6%, accuracy of 93.5%, recall of 92.8%, and precision of 91.4%. With a 95% accuracy rate, 98% F1 measure, 94% precision, and 93% recall, the RCNN model functioned effectively. The result showed the proposed method achieved better performance in athlete injury detection and accurately recognizing all rehabilitation monitoring. This study provides a complete approach to athlete health management by highlighting the integration of rehabilitation monitoring and injury detection into an overall structure.

Keywords: athlete injury detection; rehabilitation monitoring; biomechanics; wearable device; adjustable recurrent neural network (ARNN); redefined convolutional neural network (RCNN)

1. Introduction

Wearable technologies have revolutionized sports science by providing real-time, data-driven insights into biometrical dimensions, injury risks, and recovery processes. In the new era, wearable devices like smartwatches, specialized sports gear, and fitness trackers are equipped with sensors and they have changed the way athletes are monitored and improved at both competitions and training sessions [1]. Wearables can collect very detailed biomechanical data, such as joint angles, muscle activation, and movement patterns, as well as heart rate information; therefore, wearables have been accepted recently as a tool for athletes to have a comprehensive view of their physiological status [2]. One of the major challenges in sports is the early detection of injuries. Many sports injuries result from gradual wear and tear, poor technique, or overuse; warning signs often manifest subtly in an athlete's biomechanics. Wearable technology addresses these issues by providing continuous feedback on key metrics that can catch changes in movement patterns or performance, which may indicate the onset of injury [3]. Machine learning (ML) techniques such as recurrent neural network (RNN) and other deep learning (DL) algorithms, are particularly applicable to the large and complex datasets wearable devices generate. These algorithms can find patterns in the records that could not be directly visible to the human eye [4]. By learning from previous injury data and movement patterns, the algorithm will build predictive models of the likelihood of injury, thus enabling proactive interventions [5]. Apart from injury detection, a wearable is also very effective in monitoring the rehabilitation process post-injury. In such a rehabilitation situation, it becomes very crucial to ensure that monitoring will take place to make sure athletes regain full functionality of the affected areas and do not make any premature return to rigorous competition, since recurrence of injuries may occur [6]. Wearable devices can monitor key rehabilitation metrics such as range of motion, strength, stability, and overall movement quality. Wearable devices track an athlete's performance to provide instantaneous feedback so that rehabilitation protocols may be modified in response to the athlete's recovery status [7]. Biomechanical data captured during rehabilitation can be compared to pre-injury data to provide a more accurate determination of when an athlete is ready to return to full participation in their sport [8]. The integration of wearable technology with advanced analytics in modern sports science offers a tool that is unparalleled in its potential to achieve significant improvement in athlete safety, performance, and longevity [9]. Through wearables, there is a real-time, data-driven insight into injury prevention and rehabilitation, thus enabling athletes and coaches, together with medical experts, to make informed decisions that improve the outcomes [10].

This paper is dedicated to developing and testing sophisticated ML techniques, such as adjustable recurrent neural network (ARNN) and redefined convolutional neural network (RCNN), by applying them to wearable sensor data for injury risk detection and monitoring the rehabilitation process in athletes to improve performance and recovery.

Key contribution:

- It contributes to the increasing integration of ML algorithms for injury detection and rehabilitation monitoring using wearable technology in athletes.
- The ARNN is used to detect the possibility of injury, such as unusual joint movements, by enhancing the accuracy of biomechanical data analysis.
- In the technique for effective monitoring of the rehabilitation process, the RCNN is used.

The research is organized as follows: Section 2 is dedicated to related works about athlete injury detection and rehabilitation. Section 3 defines the methodology, including data collection, data preprocessing, feature extraction, ARNN model, and RCNN model. Section 4 presents the results of the work, showing the performances of the different models. Section 5 discusses the findings, and Section 6 concludes the study with key insights and possible future directions.

2. Related works

Predictive ML could be used to identify an athlete's injury risk variables based on data, as demonstrated by [11]. The process could potentially be used to generate new risk factor theories. The prediction of moderate and severe knee and ankle injuries was done using both linear and non-linear approaches. The outcomes demonstrated that the estimation of a future injury was a very difficult task; however, even the low predictive power models were able to detect constantly some predictive factors of injury risk. The developed an intelligent badminton training robot (IBTR) to prevent badminton player injuries using the ML technique [12]. The athletes' movements were identified and analyzed through the use of the hidden Markov model, which was developed by the integration of hardware and software components into an IBTR. To evaluate the model's performance, a computer simulation was carried out. Finally, the identification rate and precision of the developed IBTR were assessed. Based on a basketball intelligent robot [13] improved the efficiency in the practical adoption of basketball training strategies. Additionally, their approach prevented acute or chronic injury caused by collisions and blind training. Initially, a preliminary analysis was conducted for sport recognition in basketball practice in conjunction with a basketball movement trajectory model. The research led to the establishment of a mathematical model for shooting movement trajectory in basketball movement as well as an analysis of the factors that influence the shooting. In their experimental study [14] created an innovative dual-branch aerobic exercise injury risk prediction system using big data and computer vision technology. Big data analysis demonstrated that valuable features could be extracted from competitive data in aerobics. By combining a CNN with visually recognized aerobics images, they were able to diagnose the athletes and assess their physical growth as well as their level of fitness. At last, the scientific level of aerobics training was improved. They proposed a state-of-the-art DL method called the Multiple bidirectional Encoder Transformers for Injury Classification (METIC) system to forecast upcoming hunts based on earlier hunts, player statistics, and game activity [15]. They also gathered longitudinal data on NBA player injuries through public data sources. The proposed METIC model performed much better than other conventional ML approaches. The suggested model could be used by both the practitioner and the front office for better management of the athletes and reduction in injury incidence.

They proposed a Deep Learning-assisted System (DLS) using cloud computing and the Internet of Things (IoT) to diagnose sports injuries [16]. The research applied IoT sensors to collect the key data to diagnose sports injuries. Conversely, cloud computing was used for adaptable processing power and resources in computer systems. The study enhanced the athlete health rehabilitation program by examining the framework for monitoring brain damage using an appropriate neural network to anticipate the diagnosis of brain injury. Discussed that wearable technologies could enhance health conditions and athletic performances in athletes by monitoring participants in various variables. In the research, they used wearable technology such as Zephyr Bio Harness for gathering computable information to produce insights that would forecast and prevent wearers' physical exertion during sportive activities [17]. Most surprisingly, the results revealed that an integration of high mechanical load and high body mass index (BMI) might lead to injury. Hence, when designing the workout program, an important decision was made to gradually increase the mechanical load throughout the practice season as the fitness level of the athletes improved. They proposed an IoT and blockchain-based sports injury risk neural network analysis system. The system was integrated with a multi-sensor data fusion technique that performed a comprehensive analysis of sports injuries [18]. Sensors monitored and collected data regarding the recovery of athletes from sports injuries. Hence, the system determined the values for the corresponding output of a neural network and, by referencing the hazard level table, provided an assessment of the athletes' risk levels. The experimental results indicated that the integration of IoT, neural networks, and blockchain technologies could render the suggested sports injury rehabilitation monitoring system helpful in the prompt recognition of damage positions.

They proposed a novel technique in terms of forecasting football players using wearable technology and RNN. The health status of the players was monitored in real-time by the proposed system [19]. The health prediction results were generated after the input of time-step data into an RNN. Various trials were conducted during the study, and the results were obtained based on the information gathered regarding the health status of the players. The simulated results showed that the proposed methodology was very practical and reliable. A method for visual inspection of technology in sports injury detection was developed by Chen and Yuan [20]. To investigate two-dimensional imageries of one-dimensional interval sequences and then convert the one-dimensional interval sequence acquired by the sensor into two-dimensional imageries, the time-frequency diagram of the sensor data was utilized as the input for the CNN model. According to the sensor data, they were able to improve their use of CNN and computer vision technology and obtain new insights. The model has incredible success in extracting features at different scales. The football participant's injury full-cycle Management and Monitoring System (MMS) was developed by Pu [21] by integrating the blockchain and ML approach. Players' activity information was gathered, maintained, cleaned out, mined, and displayed through blockchain and ML advancements. Intelligent ways to assist football players recover from injuries were also developed using ML. The suggested model maintained larger amounts of information than the conventional approaches. The Wireless Sensor Network (WSN) based monitoring system constructed by Hui [22] arranged sensor nodes in fundamental parts of exercisers, such as joints, to gather real-time gesture records meanwhile, machine vision technology was integrated with WSN to process and analyze the collected data to identify incorrect motion posture. A WSN integrated with machine vision technology was capable of preventing sports injuries. The suggested method significantly increased the accuracy of monitoring compared to the traditional methods.

3. Methodology

Data was gathered from the wearable's dataset, taken from Kaggle, and pre-processed by a Gaussian filter to reduce the noise. After that, feature extraction was done by employing Independent Component Analysis (ICA), which reduced the dimensions of the data. After that, anomaly detection was done by using the Adjustable

Recurrent Neural Network (ARNN), and the Redefined Convolutional Neural Network (RCNN) was utilized for monitoring the rehabilitation. The obtained results are compared to verify the efficiency of both models in the processes of detecting anomalies and the monitoring of rehabilitation progress in patients. **Figure 1** demonstrates the overall flow of the research.

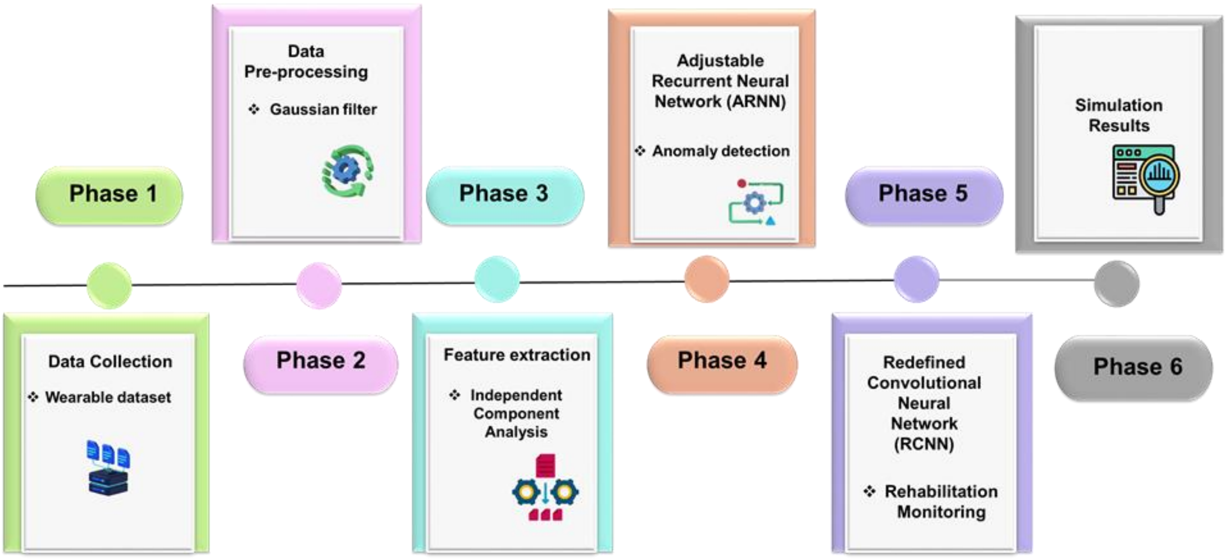


Figure 1. The general flow of the research.

3.1. Dataset

The Wearables Dataset available in Kaggle contains data from various wearable devices, including accelerometer and gyroscope data. It captures sensor data concerning the physical activities that can be used for the analysis of motion patterns and anomaly detection. This dataset will carry much importance in injury detection and rehabilitation monitoring algorithms since it provides real-time measurement of motions and orientations. It can be openly accessed, which makes it suitable for practical use in research and development with consideration of analytics on wearable devices. There are 40 attributes are gathered, and these characteristics are helps to identify athlete injuries.[23]

3.2. Preprocessing using Gaussian filter

Biomechanical sensor data from wearable devices are smoothened by the Gaussian filter, refining data quality that injury detection accuracy and effective monitoring of rehabilitation rely on. This biomechanical sensor data is smoothened with a Gaussian filter in a process attempting to reduce the effect of noise and irregularities within. This is important because by denoising the signals, the clarity of the signal is reinforced, hence enabling subtle patterns and anomalies to be found in the signals for potential injury detection and rehabilitation assessment. In the context of an injury detection algorithm, clearer data could enable abnormal joint movements or other indications of risk to be pinpointed far more precisely. In rehabilitation monitoring, such a filter supports better quality signals to track correctly the exact progress of an athlete and his or her compliance with prescribed exercises. Hence, this Gaussian filter is indispensable in ensuring the reliability and effectiveness of the wearable technology system by providing high-quality data for subsequent analysis and decision-making.

It is a linear filter in which each data point has a weighted value based on the shape of the Gaussian function. It is chosen because this method can refine biomechanical signals by filtering out noise, an important step toward achieving appropriate data analysis. The Gaussian filter has a kernel center that focuses more on proximal rather than distant data points, which greatly enhances efficiency during the removal of normally distributed noise in wearable device data.

Wearable sensor readings often have noise within the data, due to movement artifacts or other environmental interferences. This Gaussian filter further cleans the data to present a signal that truly stands for biomechanical movement patterns and not merely random fluctuations. This would improve the performance of the injury detection algorithm by reducing false positives or missed injuries triggered by noisy data.

Each value of an element in a Gaussian smoothing filter can be computed by using Equation (1).

$$g(w,z) = \frac{1}{d} e^{\frac{w^2+z^2}{2\sigma^2}} \tag{1}$$

where σ indicates the average deviation of the Gaussian kernel and d is a normalization constant, which makes the scale of the filtered data the same as that of the original. This ensures that the smoothed data represents the biomechanical signals, which is necessary for reliable injury detection and rehabilitation tracking.

3.3. Feature extraction using independent component analysis (ICA)

ICA plays a major role in processing wearable sensor data for athletes since it isolates the mixed biomechanical signals into different independent components. The separation is necessary for increasing the accuracy at which injury and rehabilitation monitoring are considered. In the context of wearable technology, various biomechanical signals may be intertwined in the way that different sensors capture them, such that accurate identification of a pattern or anomaly specific to injury risk or recovery progress can hardly be performed. ICA decomposes varied signals into separate, statistically independent components, which enables the isolation of the relevant features against the noise and interference present in the data. ICA increases the accuracy of detecting abnormal joint movements and monitoring rehabilitation exercises by refining signal features with higher clarity and specificity. Such refined feature extraction allows for more appropriate assessments and interventions which will lead to better health management among athletes and more effective rehabilitation results.

In the domain of the analysis of wearable device data, the correspondingly generic computation methodology is a multivariate analysis that separates complex biomechanical signals collected from multiple sensors into additive subcomponents. Data coming out of wearable devices can be mathematically represented as given in Equation (2).

$$W = BT \tag{2}$$

where, W = matrix of m observed signals, with each signal being associated with the data from a specific sensor, $W = [w_1, \ldots, w_m]^S$, T represents the matrix of the n underlying biomechanical patterns, $T = [T_1, \ldots, T_n]^S$ and B is assumed to be the mixing matrix which defines the contribution of each independent signal in the observed signals. It can be modeled as an $[m \times n]$ matrix.

The number of Independent Components (ICs) shall be calculated by calculating the un-mixing matrix X, which is given in Equation (3).

$$T = XW \tag{3}$$

The computation of X requires centered and whitened data. Centering is done by subtracting from the data the average value of each observed signal. That centers the underneath biomechanical signals around zero. Whitening is a linear transformation of the sensor signals matrix W into another matrix W^- such that the signals become uncorrelated.

One of the most usual whitening procedures is carried out with the use of eigenvalue decomposition of the covariance matrix. It can be expressed as it is shown in Equation (4).

$$FFW^S = FCF^S \tag{4}$$

where F is the orthogonal matrix consisting of the eigenvectors of the covariance matrix FFW^S and $C = diag(c_1, c_2, \ldots, c_m)$ is the diagonal eigenvalue matrix of C. Now the whitened matrix W^- may be obtained by the expression as shown in Equation (5).

$$W^- = FC^{-\frac{1}{2}}F^S W \tag{5}$$

Whitening on the unmixing matrix X is done as in Equation (6).

$$\hat{T} = XW = XFC^{-\frac{1}{2}}F^S W^- = X^- W^- \tag{6}$$

This whitening stage allows minimizing the number of parameters that have to be estimated for the unmixing matrix X, which is shown in Equation (7).

$$X = X^- FC^{-\frac{1}{2}}F^S \tag{7}$$

X^- is orthogonal and enables the optimal separation of the biomechanical signals from sensor data. It allows injury detection and monitoringin an optimum way. The mixing matrix B can finally be computed by Equation (8).

$$B = (X^S X)^{-1} X^S \tag{8}$$

This approach will enable the separation of critical biomechanical components from noisy multi-sensor data, thus allowing more comprehensive identification of movement patterns associated with injury risk and tracking recovery progress throughout rehabilitation.

3.4. Anomaly detection using adjustable recurrent neural network (ARNN)

The Adjustable Recurrent Neural Network (ARNN) is an advanced injury risk monitoring system where sequential biomechanical data will be collected from different wearable sensors. It works exceptionally well in the identification of abnormal behavior by focusing on unusual movements within an athlete's joints. One major strength of an ARNN is that it can adapt with time; this takes place through changeable parameters, which adjust as movement patterns evolve. With such flexibility in the ARNN, it is capable of determining in which phase there is a deviation from normal joint movement, with greater injury risk or improper technique. While continuously tracking dynamic biomechanical data, the ARNN now provides prompt alerts and insights for early intervention that will help prevent injuries and improve athletic performance. It is important given health and safety concerns for the athletes while training and competing. **Figure 2** shows the schematic layout of ARNN, which consists of three layers. These three levels are known as the input, output, and hidden layers.

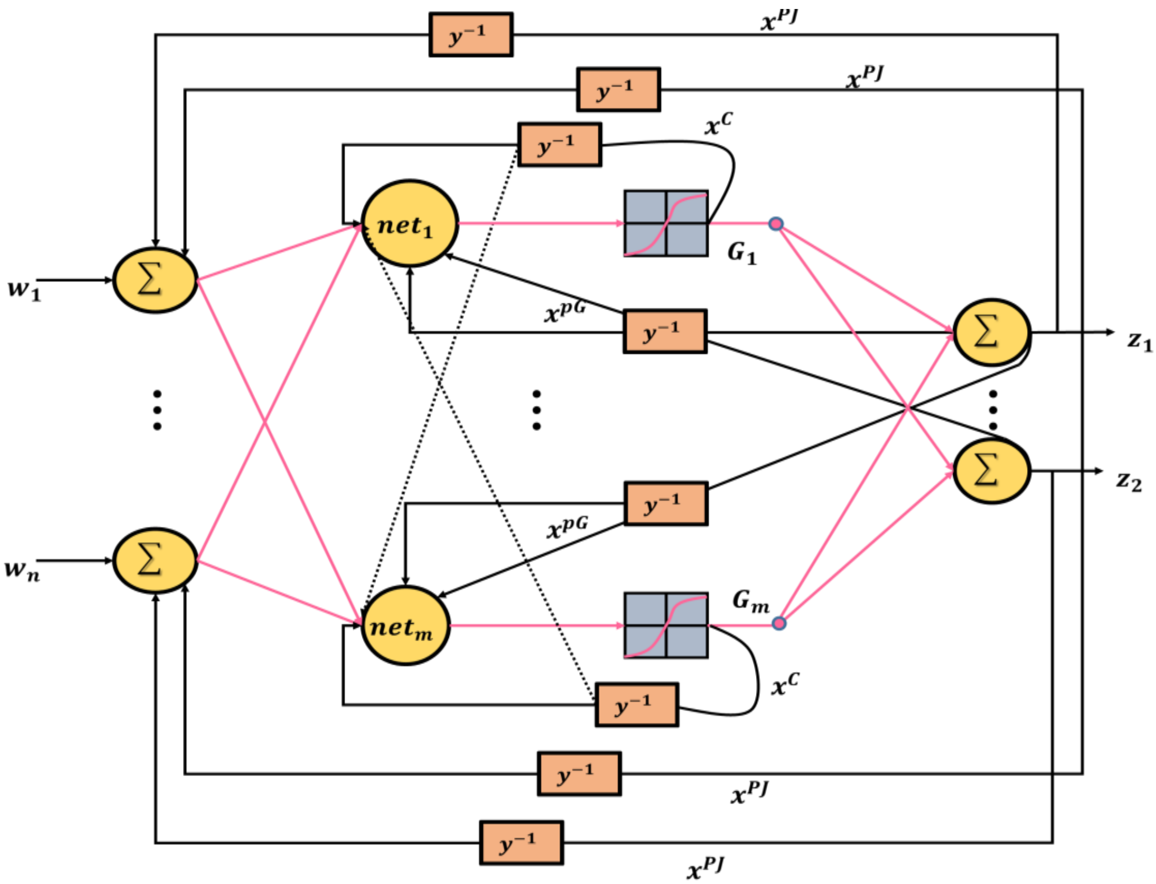


Figure 2. Structure of ARNN.

The input layer's neurons are composed of both their input signals and the output layer's feedback signals, whereas the neurons in the hidden layer are composed of neuron signals transmitted from the input layer, feedback signals from the output layer, and their specific feedback signals modified by the activation function. The neurons in the output layer are covered by neuron signals that are relayed from the hidden layer. Since the activation function of the hidden layer is an inverse square root function, ARNN functionality can be achieved by modifying the hidden layer's output by the α parameter through the neuron signals of the activation function. Each layer is specifically explained as follows:

Input Layer: within the ARNN, the input layer is made up of n neurons, and the output of the input layer is made up of the output layer feedback data in addition to the altered data of the n input layer neurons. Equation (9) can be employed to define the formation of the input layer.

$$\Lambda_j = w_j + \sum_{l=1}^{q} y^{-1}(z_l)\omega_{jl}^{pJ} B = (X^S X)^{-1} X^S \quad (9)$$

where $j = 1,2,\ldots,n$. The variable $w_j \in \mathbb{R}^n$ denotes the input signal and $y^{-1}(z_l) \in \mathbb{R}^o$ denotes a one-step delay during which the ARNN's output signal feeds back to the input layer neuron. The output layer's input layer is linked by output feedback weights, which are represented by $\omega^{pJ} \in \mathbb{R}^{n\times o}$.

Hidden Layer: The term m refers to the neurons in the hidden layer. These neurons receive feedback from every output layer neuron in addition to the transmitted signals from the input layer. They also receive self-feedback signals from all hidden neurons that have been converted by the activation function. Equation (10) can be used to define a hidden layer neuron.

$$net(j) = \sum_{i=1}^{n} \Lambda_i \omega_{ji}^{J} + \sum_{l=1}^{m} y^{-1}\big(G(j)\big)\omega_{jl}^{C} + \sum_{k=1}^{q} y^{-1}(z_k)\omega_{jk}^{pG} \quad (10)$$

where $j = 1,2,\ldots,m$, the activation function-computed one-step delayed self-feedback signal of the hidden layer is represented by $y^{-1}\big(G(j)\big)$. The self-feedback weights of the one-step delayed signals in the implicit layer, the feedback weights connecting the output and implicit layers, and the weights connecting the input and implicit layers are denoted by the symbols $\omega^J \in \mathbb{R}^{m\times n}$, $\omega^C \in \mathbb{R}^{m\times q}$, and $\omega^{pG} \in \mathbb{R}^{m\times q}$, respectively.

Equation (11) can be used to describe the output of a neuron in the hidden layer since its activation function is the inverse square root function.

$$G(j) = e_b\big(net(j)\big) = \frac{net(j)}{\sqrt{1 + \alpha net(j)^2}} \quad (11)$$

where α is the activation function adjustment parameter. This allows the neural network to be tunable by freely modifying the parameter b, which in turn allows the activation function to take on diverse shapes in response to varying task requirements and data distributions. Furthermore, the inverse square root function is advantageous for gradient computation and backpropagation since it is continuous and smooth throughout a range of input values, aiding the neural network in identifying complex structures in the data.

Output Layer: Equation (12) illustrates how the inputs to the output layer are determined by the weighted amount of the outputs supplied by the hidden layer.

$$z = u^S G(\Lambda, \omega^{pJ}, \omega^J, \omega^C, \omega^{pG}) = u^S G \quad (12)$$

In the present scenario, the weights that link the neurons of the hidden layer and the output layer are represented by $u \in \mathbb{R}^{m\times q}$.

3.5. Redefined convolutional neural network (RCNN)

Rehabilitation monitoring performed by the Redefined Convolutional Neural Network (RCNN) analyzes the biomechanical data acquired from wearable sensors, including both motion and muscle activity. It processes these data in the RCNN to identify and interpret patterns indicative of the athlete's progress toward recovery. These trends can be inspected by the RCNN for the development of the quality of movement, range of motion, and stability in various aspects. With the ability to analyze such factors, the system can provide specific feedback and adjust rehabilitation protocols according to what is adjudged best for the progress of the individual. Thus, the effectiveness of the rehabilitation process is further enhanced by such a tailored approach, whereby interventions become responsive to an individual's trajectory and overall outcomes.

Conventional CNN is improved at the fully connected layer with two penalty terms in the cost function to increase the performance of RCNN in rehabilitation monitoring by taking rehabilitation session recency and frequency into consideration. The mean cross-entropy error function, which is defined as follows in Equation (13), is often minimized to make it possible to train CNN.

$$K(\theta) = \frac{1}{M}\sum_{j=1}^{M} \mathrm{cost}_j,\ \mathrm{cost}_j = -\sum_{i=1}^{S} s_{ji} \log(z_{ji}) \tag{13}$$

where M is the dimension of the batch, and S is the total of periods. Here,cost_j denotes the cost function of sample j, while s_{ji} and z_{ji} stand is for the true value and output probability of class i for sample j, respectively. A modified cost function is defined which includes rehabilitation recency q_j and rehabilitation frequency e_j, specified in Equation (14), where the penalty terms are initialized from a trimmed standard distribution and adjusted through training.

$$\mathrm{cost}_j = -\sum_{i=1}^{S} s_{ji} \log(z_{ji}) - \omega_1 q_j - \omega_2 e_j \tag{14}$$

Rehabilitation recency Q_j for a subject j participating in rehabilitation session $t.month$ is defined in Equation (15) as the time interval between the current session and the last rehabilitation session attended by the subject. This is given as the inverse of the time difference between the two sessions.$month$ and $t.month$.

$$Q_j = \frac{1}{q.month - t.month + 1} \tag{15}$$

The symbol E_j is the rehabilitation frequency, representing the number of sessions completed by the subject before the current session; similarly, both Q_j and E_j are scaled to comparable values by Equation (16), ensuring balanced influence on the model to enhance the ability of the monitoring system for effective tracking of rehabilitation progress.

$$q_j = \begin{cases} 0 & \text{if } Q_j < Q_{min} \\ \dfrac{Q_j - Q_{min}}{Q_{max} - Q_{min}} & \text{if } Q_{min} \le Q_j \le Q_{max} \\ 1 & \text{if } Q_j > Q_{max} \end{cases}$$

$$e_j = \begin{cases} 0 & \text{if } E_j < E_{min} \\ \dfrac{E_j - E_{min}}{E_{max} - E_{min}} & \text{if } E_{min} \leq E_j \leq E_{max} \\ 1 & \text{if } E_j > E_{max} \end{cases} \tag{16}$$

4. Result

The proposed approach is implemented using Python (v 3.12) on Windows 10 OS. The system is driven by an Intel Core i5 processor and features a high-performance IRIS graphics card, which delivers a strong capacity for executing ML applications.

Here, the proposed Adjustable Recurrent Neural Network (ARNN) is compared with existing methods such as AdaBoost-Random Forest (Ada-RF), Random Forest (RF), and Bayesian (BN) [23]. Similar to this, Redefined Convolutional Neural Network (RCNN) is also evaluated using metrics like precision (%), F1-measure (%), accuracy (%), and recall (%) against other methods like Support Vector Machine (SVM), Recurrent Neural Network (RNN), and Deep back propagation-long short-term memory (Deep BP-LSTM) [24].

4.1. Accuracy

Sufficient healing depends on accurate monitoring of therapy and injury identification in athletes. Using innovative methods, like wearable sensors and ML techniques, improves the accuracy of detecting injuries and monitoring the course of rehabilitation. This guarantees that athletes receive timely interventions and individualized training modifications, which ultimately leads to safer and more effective achievements. The output of accuracy for ARNN and RCNN is shown in **Figure 3**. And the output of accuracy for ARNN is shown in **Figure 3a**, RCNN is shown in **Figure 3b**. The result demonstrates that the suggested ARNN (93.5%) approach outperforms the existing methods such as Ada-RF (86.9%), RF (81%), and BN (77.5%). Similarly, the proposed RCNN (95%) achieves superior performance over existing methods such as Deep BP-LSTM (92%), RNN (89%), and SVM (90%).

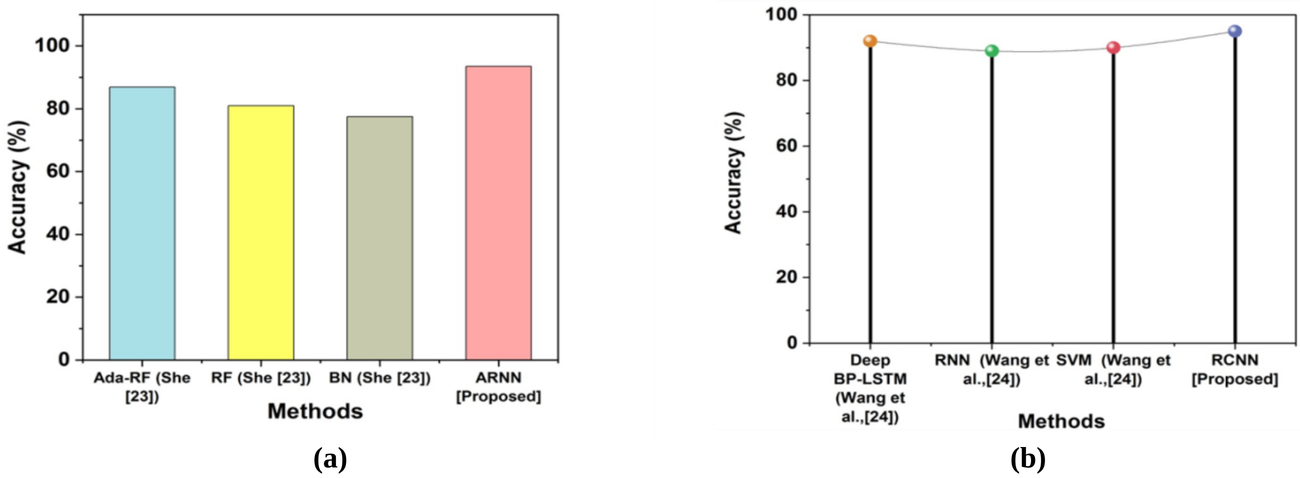
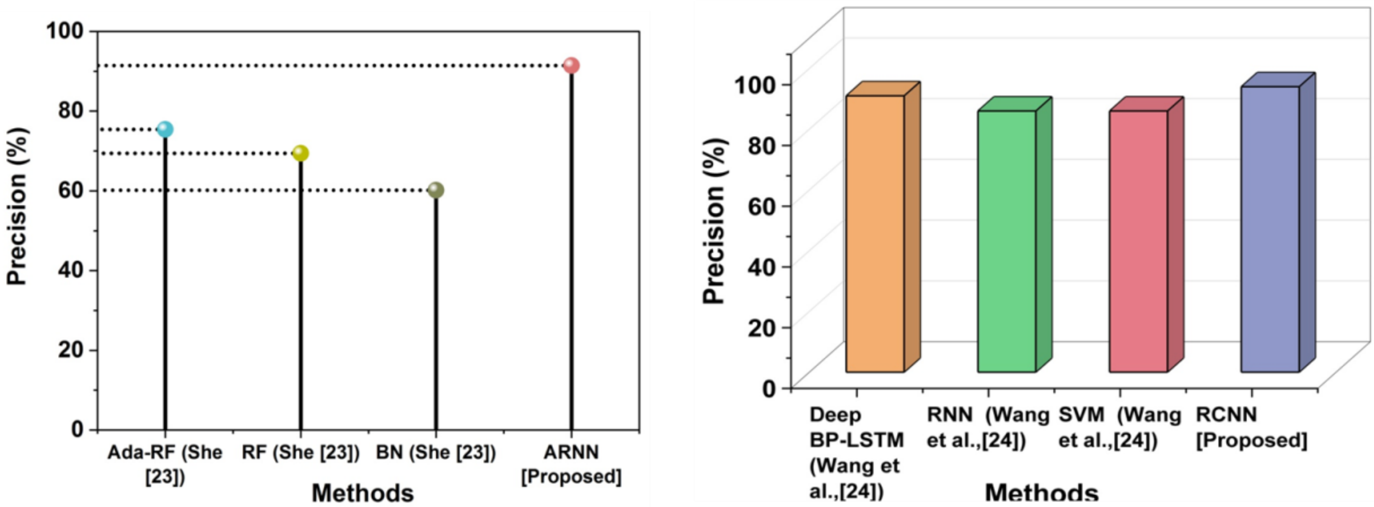


Figure 3. Accuracy results. **(a)** Anomaly detection; **(b)** rehabilitation monitoring.

4.2. Precision

The precise diagnosis of injuries and gauging healing progress, wearables, and data analytics are two examples of innovative technologies used in athlete injury diagnosis and rehabilitation monitoring. This method reduces the chance of reinjuring while improving individualized treatment programs, streamlining rehabilitation procedures, and eventually assisting athletes in reaching their maximum potential. **Figure 4** displays the output of precision for ARNN and RCNN. And **Figure 4a** displays the output of precision for ARNN, **Figure 4b** displays the output of precision for RCNN. The outcome shows that the proposed ARNN (91.4%) method performs better than existing methods such as Ada-RF (75.4%), RF (69.4%), and BN (60.2%). Similarly, the proposed RCNN (94%) performs well when compared to existing methods such as Deep BP-LSTM (91%), RNN (86%), and SVM (86%).

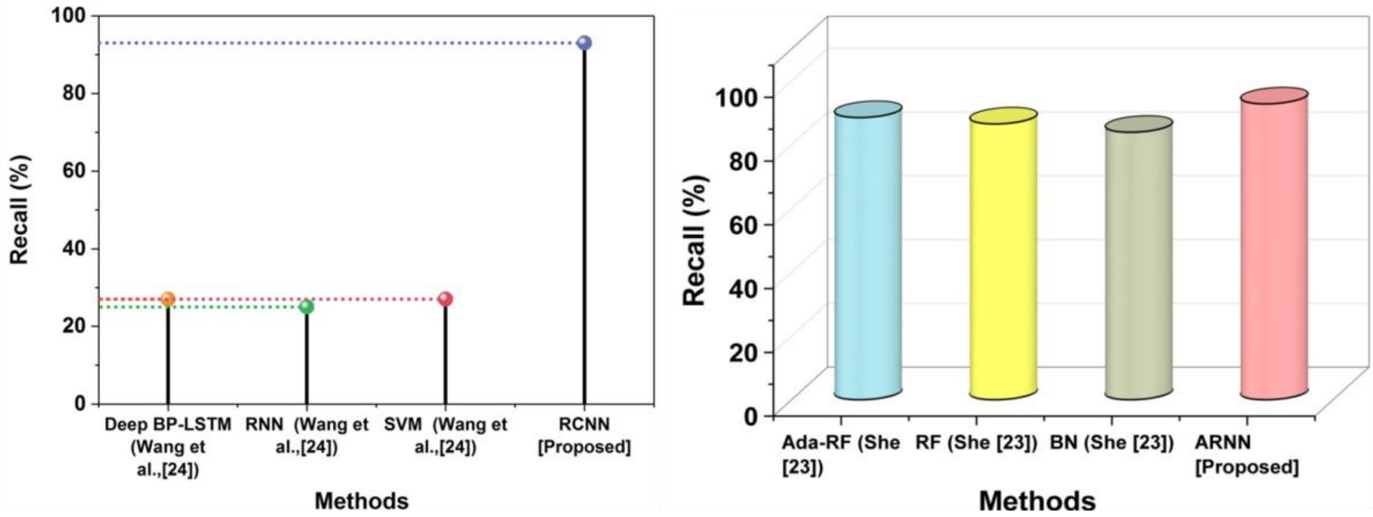


(a) (b)

Figure 4. Precision results. **(a)** Anomaly detection; **(b)** rehabilitation monitoring.

4.3. Recall

It refers to the proportion of actual injury risks identified correctly. High recall ensures that most of the true injury risks are detected, which is important to avoid missed detections during rehabilitation monitoring. Athlete injury identification and recovery monitoring depend heavily on recall. It refers to the capacity to precisely recognize prior injuries and evaluate the state of recuperation. Enhancing individualized rehabilitation procedures with effective memory enables customized therapies that lower the risk of another injury during competition and exercise and improve athletes' recovery results. **Figure 5** displays the output of recall for ARNN and RCNN. And **Figure 5a** displays the output of recall for ARNN, while **Figure 5b** displays the output of recall for RCNN. The result proves that the proposed ARNN (92.8%) technique performs better when compared to existing approaches such as Ada-RF (88.5%), RF (86.5%), and BN (83.9%). Similarly, the proposed RCNN (93%) outperforms the existing methods such as Deep BP-LSTM (27%), RNN (25%), and SVM (27%).



(a) (b)

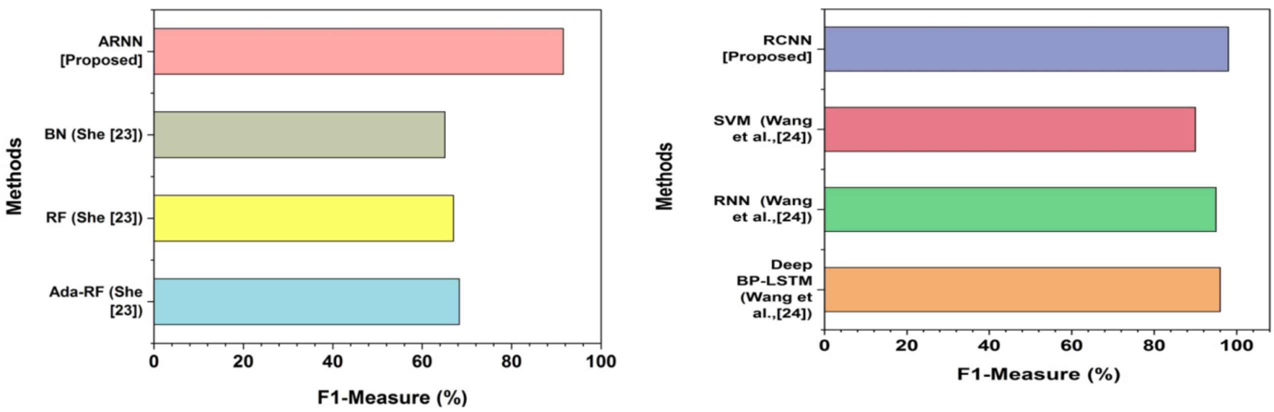
Figure 5. Recall results. **(a)** Anomaly detection; **(b)** rehabilitation monitoring.

4.4. F1-measure

The assess a model's efficacy in identifying athlete injuries and tracking their recovery, the F1-measure combines recall and accuracy. To effectively monitor and promptly intervene in athletes' recovery processes, ensures that positive results and false negatives are minimized. This comprehensive evaluation of the reliability of a model is provided. **Figure 6a** and **Figure 6b** display the output of the F1-measure for ARNN and RCNN, respectively (see **Figure 6**). The result demonstrates that the proposed ARNN (91.6%) technique outperforms the existing methods such as Ada-RF (68.3%), RF (67%), and BN (65.1%). Similarly, the proposed RCNN (98%) performs better when compared to existing methods such as Deep BP-LSTM (96%), RNN (95%), and SVM (90%). **Table 1** shows the numerical values of ARNN and RCNN.

Table 1. Numerical results of proposed ARNN and RCNN.

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-measure (%)
For anomaly detection (ARNN)	93.5	91.4	92.8	91.6
For rehabilitation monitoring (RCNN)	95	94	93	98



(a) (b)

Figure 6. F1-measure results **(a)** anomaly detection; **(b)** rehabilitation monitoring.

5. Discussion

Most of the existing approaches for injury detection, such as Ada-RF, RF, and BN [24], suffered from significant drawbacks when it came to the analysis of complex biomechanical data from athletes. Among these, Ada-RF, which was used to boost the performance of Random Forest, was often subject to overfitting in case the dataset was either characterized by high-dimensional features or noisy data. Poor generalization was the consequence of this overfitting, resulting in reduced effectiveness in real-world applications. Although RF was a very powerful ensemble technique, it was also used to overlook the temporal dependencies in sequential data, which were of paramount importance for the modeling of the dynamic nature of biomechanical movements. Furthermore, most RF variants overfitted to noisy data, thus making those predictions even less reliable. BN assumed feature independence, which was hardly the case in biomechanical data, where joint movements and other features were often interdependent; hence, BN provided poor injury risk predictions.

The current models have poor predictive ability, making it challenging to anticipate future injuries. Despite identifying risk factors, overall reliability is low, indicating that the complexity of injury risk variables is not well captured [11]. Acquiring comprehensive past injury data for every athlete might prove difficult since the METIC system could need it again [15]. The effectiveness of the model might be limited in its ability to generalize across other sports or leagues and is dependent upon the quantity and accuracy of player and game activity data that are gathered. The ARNN is capable of adaptively learning from a variety of datasets to improve prediction capacity and efficiently capture complicated injury risk indicators. A better generalization across sports is achieved by the RCNN, which can extract complex characteristics from player activity data. When used in combination, these models make strong, reliable forecasts for injuries by using a wealth of precise data.

Here, the proposed ARNN model overcomes such limitations by exploiting temporal memory for tracking and learning sequential dependencies in the movement of joints of athletes. This leads to more accurate anomaly detection, such as abnormal joint movements, since the ARNN model captures the spatial and temporal correlations in the data. For this reason, ARNN can achieve much improvement in the overall robustness of injury risk detection by improving both precision and recall.

Similarly, in the case of rehabilitation monitoring, existing approaches had some problems. Deep BP-LSTM [24] could handle long-term sequences, but high computational resources were required, and vanishing gradient problems badly affected the training process in the case of complex rehabilitation exercises. Although RNN [24] was useful for time-series data, unstable gradients hamper its usability in longer dependencies. This resulted in lower accuracy as time increased. Originally designed for static classification, SVM [25] was inefficient in dealing with dynamic data that included a time factor—such as rehabilitation progress. These are provided by the redefined CNN, which efficiently processes both spatial and temporal information. RCNN minimizes computational complexity while tracking the progress of rehabilitation with high accuracy; this ensures the correctness of monitoring and validation across exercises. This ability to handle both dimensions lead to improved accuracy and faster convergence during training; hence, it is more appropriate for monitoring athlete rehabilitation.

- Improved Education Using Various Data With the ability to adapt to varied datasets, ARNN can enhance its predicting powers in a variety of scenarios and athlete types.
- Capturing Temporal Dependency Because ARNN and RCNN are made to take temporal dependencies in consideration, it is possible to represent biomechanical motions more accurately, which is important for predicting injuries.
- Complicated Feature Extraction More precise detection of injury risk variables is made possible by RCNN's exceptional ability to identify complex patterns and correlations from player activity data.
- Enhanced Broadcasting Ability By addressing the shortcomings of previous approaches, which frequently overfit particular datasets, these models are designed to generalize better across other sports and leagues.
- Resilience in the presence of Noise Even in the face of data anomalies, the framework of ARNN and RCNN is optimized to process noisy data more efficiently and produce more dependable predictions.
- Extensive Risk Evaluation With the combined method, the capacity to collect complex injury risk factors is improved, leading to more accurate forecasts for injury prevention by utilizing the capabilities of both systems.

6. Conclusion

The proposed IDRM system is a tremendous revolution not only due to the integration of the most advanced neural network models with wearable technology but also to the incorporation of ICA for feature extraction and Gaussian filtering for data pre-processing. The ARNN detects risks of injury, especially the chances of hyperextension injury to the joints, with very high-performance metrics, achieving 93.5% accuracy, 91.4% precision, 92.8% recall, and an F1-measure of 91.6%. Such performance indicates that ARNN is equally capable of detecting potential injuries accurately to raise timely alerts. The RCNN has worked well in monitoring the rehabilitation process, resulting in superior results with metrics at 95% for accuracy, 94% for precision, 93% for recall, and an outstanding F1-measure of 98%. These metrics present an aspect of the viability of RCNN for rehabilitation tracking and protocol compliance follow-up. However, despite its strength in delivering advanced features, IDRM does have some notable limitations relating to high computational intensity and sensitivity to noisy data. The computational cost associated with processing large volumes of biomechanical data and running complex neural network models can be at a higher end. Future research should be focused on making the system more computationally efficient and less sensitive to noise to further broaden the applicability of the system for various types of injuries and real-time monitoring in general. Future research for the ARNN and RCNN can be used to build multi-modal strategies that integrate additional sensor inputs, improve adaptation for a variety of sporting groups, and integrate data analytics for preventative injury prevention. Enhanced model interpretability and tailored training suggestions based on unique recovery trajectories can also be investigated in future studies.

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