Rev.int.med.cienc.act.fís.deporte - vol. 24 - número 95 - ISSN: 1577-0354

Lu Z et al. (2024) GAIT ANALYSIS AND DEEP LEARNING FOR OVERUSE INJURY DETECTION IN OUTSTANDING DISTANCE RUNNERS. Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte vol. 24 (95) pp. 93-105.
DOI: https://doi.org/10.15366/rimcafd2024.95.006

ORIGINAL

GAIT ANALYSIS AND DEEP LEARNING FOR OVERUSE INJURY DETECTION IN OUTSTANDING DISTANCE RUNNERS

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Recibido 05 de Junio de 2023 **Received** June 05, 2023
Aceptado 06 de Febrero de 2024 **Accepted** February 06, 2024

ABSTRACT

Injuries caused by overuse are common in long-distance runners, and early detection of overuse-induced injuries can assist coaches in adjusting training programs to avoid further development of injuries and effectively prevent serious injuries. Gait research is an important tool in distance running research, through the athlete's gait parameters can obtain the athlete's movement status and injury. However, the traditional less research requires rich experience guidance, which is not conducive to widespread promotion. In this paper, deep learning technology is utilized to construct an athlete overuse injury gait detection model. Through the automatic analysis of the athletes less parameters to detect whether there is overuse-induced injury, early detection of injury trends, to avoid injury aggravation. Through experiments, it is verified that the model can effectively identify the gait parameter characteristics of overuse injury in excellent athletes.

KEYWORDS: Deep learning; Gait analysis; Overuse injury detection

1. INTRODUCTION

Running is one of the most popular forms of physical activity worldwide. In foreign countries, long-distance running over 3 kilometers is often highly recommended as an exercise to maintain a healthy lifestyle (Dallinga, Mennes, Alpay, Bijwaard, & Baart de la Faille-Deutekom, 2015). A survey shows that people with regular running habits in Denmark and the Netherlands account for 25% and 12.5% of their national populations, respectively (Polinder, Meerding, Mulder, Petridou, & van Beeck, 2007). And marathon has changed from a mere sport to a life goal for many people and has changed people's lifestyle to a great extent. The number of online and offline long-distance running events in China has increased rapidly, and the number of people participating in them is also growing rapidly, for example, in 2018, regular marathons in China attracted about 1.5 million people, which is an increase of as much as 500,000 people compared with 2019, and by 2020, before the outbreak of the new crown epidemic, the number had reached 3 million people (Young, 2023).

Running, as a popular form of exercise, in addition to bringing benefits such as reducing cardiovascular disease risk factors, increasing cardiorespiratory capacity, and controlling body weight, also increases the risk of skeletal muscle-related injuries. While the number of participants in long-distance running is increasing, sports injuries caused by long-distance running, especially skeletal muscle injuries of the lower limbs, have gradually attracted people's attention, and the number of injuries is huge, especially the incidence of long-distance running injuries in the general public group of non-professional athletes is very alarming. There are many long-distance runners who have experienced the problem of running lower limb injury. However, due to the fact that the occurrence of running injuries is affected by a variety of factors and there are many types of injuries, it is difficult to study the risk factors of lower limb injuries in long-distance running, and it is still not possible to clarify the main factors that cause running-related injuries. The research on sports injuries of long-distance runners in China is even more limited than that on sports injuries of professional athletes.

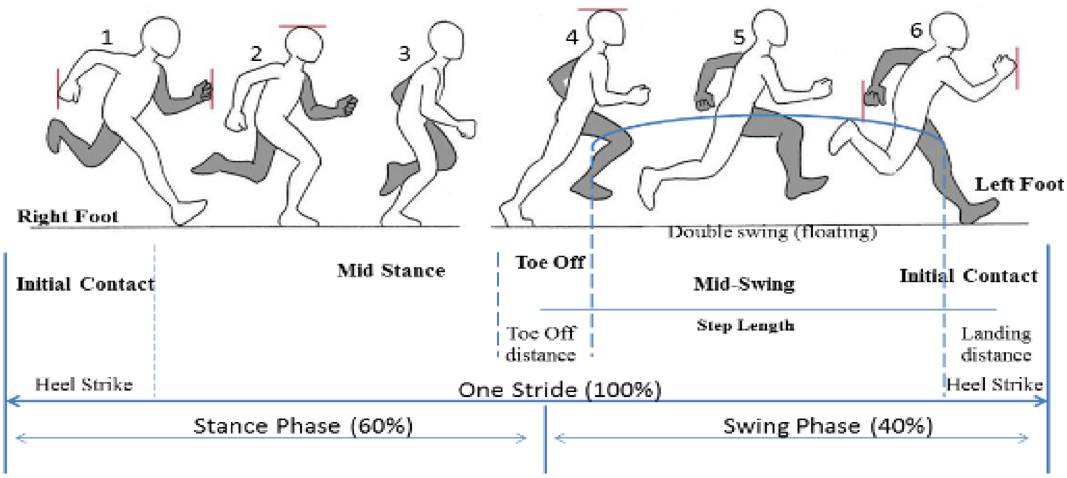

Figure 1: The gait cycle: Represents the different phases of the cycle (Kapri, Mehta, & Singh, 2021)

Gait recognition is one of the most promising biometric methods at present. The gait cycle is shown in Figure 1. However, gait recognition faces a lot of difficulties in real applications, which are mainly manifested in the fact that the human body is susceptible to the influence of external environments such as road surface, shooting angle and other walking conditions such as carriers and clothing during the walking process, resulting in strong intra-class interference in the extracted gait features (Muro-De-La-Herran, Garcia-Zapirain, & Mendez-Zorrilla, 2014). Existing gait recognition methods can be broadly categorized into two types: appearance class and model class, in which most of the appearance class methods are represented by the class energy maps generated from the gait image sequences, which can effectively describe the gait in non-continuous frames. Although this kind of methods can obtain the information of gait cycle, they are easily interfered by the change of dress. Examples of such methods are region matching identification, SPAE method , GaitGANv2 method , Gait Set method , and perspective transformation method (Chao, He, Zhang, & Feng, 2019). Model-based methods usually modularize the body structure to obtain the human skeletal feature data, which can provide information such as angular velocity. Although these methods can effectively reduce the influence of appearance changes, they are overly dependent on the stability of the model. For example, the consistent perspective transformation model method, the Hidden Markov Model method and the STDNN method (C.-T. Lin, Nein, & Lin, 1999). However, the above gait recognition techniques are more computationally intensive due to the direct use of raw coordinate data for training, and are easily affected by the absolute position of the person's location.

Deep learning technology with its powerful learning ability is playing an increasingly important role in many fields, contributing to the arrival of the intelligent era. In this paper, we construct a walking gait feature database based on the Openpose model and the feature extraction capability of human posture by convolutional neural network (CNN), extract the gait feature matrix before training, and demonstrate its specificity, stability, and the degree of correlation, so as to realize the mining of the information while reducing the amount of computation of the subsequent training, and avoiding the error caused by the difference of the absolute position of the human being each time.

2. Methodology

2.1 Data preprocessing

In the preprocessing stage, this paper firstly extracts the bones from the input color image sequence using the human pose estimation algorithm OpenPose (F.-C. Lin, Ngo, Dow, Lam, & Le, 2021). Then, the image size is cropped and uniformly scaled to a resolution of 224×224, and the skeleton is centered. Finally, the individual gait cycles of the skeletal sequence are extracted by gait cycle detection, and the SEI is calculated according to equation (1), where $I_t(x, y)$ corresponds to a single frame image and N is the number of images per gait cycle. The preprocessing flow is shown in Figure 2.

$$g(x,y)=\frac{1}{N}\sum_{t=1}^{N}I_t(x,y) \tag{1}$$

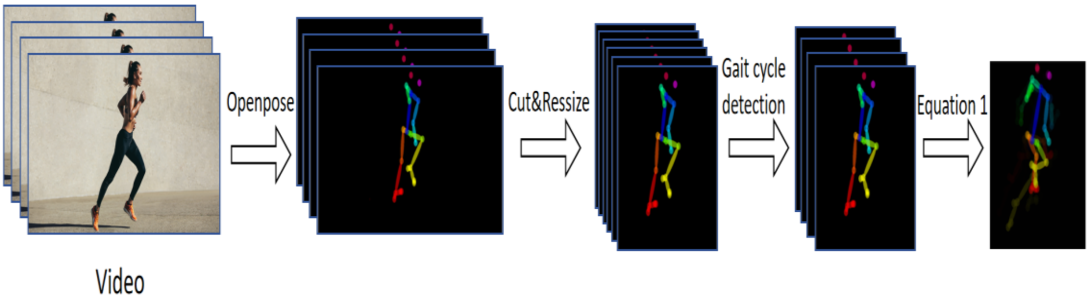

Figure 2: SEI generation process for bone energy images

2.2 Classification using lightweight attention-based CNNs

Traditional deep learning-based pathological gait analysis methods use small-scale datasets to train high-complexity models, resulting in high latency and overfitting. Therefore, this paper designs a lightweight network and further proposes an attention module to help the network focus on more informative spatial and channel features to further improve the classification accuracy.

Among several lightweight CNN algorithms, GhostNet (Wang & Li, 2022) is selected as the baseline algorithm in this paper because of its good balance between computational cost and accuracy. Based on the baseline algorithm, the model proposed in this paper improves the attention mechanism by lightweighting and dimensionality mixing, i.e., the improved GhostNet, which is shown in Figure 3.

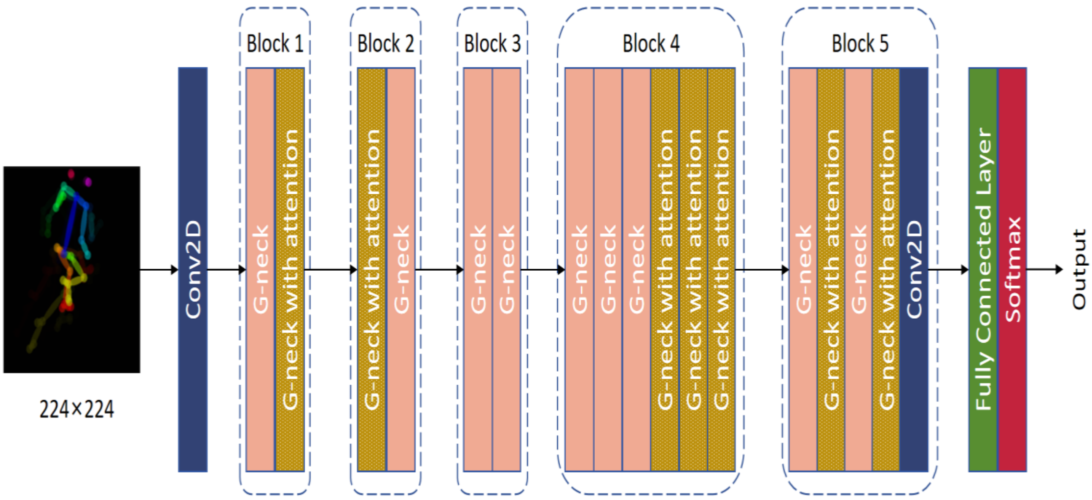

Figure 3: Improved GhostNet model structure

The entire network consists of five modules, each containing several Ghost bottlenecks (G-neck). The G-neck we use, shown in Figure 4, consists of our proposed lightweight hybrid attention module and GhostModule.

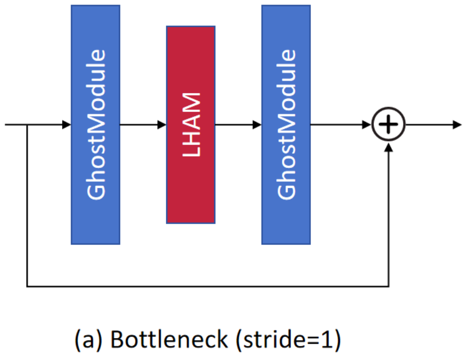

Figure 4: Schematic diagram of the G-neck module

The G-neck consists of two structures, the difference being that one of them includes an additional DWCon (deep convolution) to realize downsampling with a step size of 2. The structure of the attention module, LHAM, is shown in Figure 5. The structure of the attention module, LHAM, is shown in Figure 5. In this paper, the LHAM module is placed in some of the G-necks (e.g., G-necks 4, 5, 10, 11, 11, 12, 14, 16) to focus on important spatial and temporal feature maps. The LHAM optimizes the problem of using two fully connected layers in the SE module in GhostNet (Wang & Li, 2022), which leads to the problem of too large amount of network parameters. The specific implementation of LHAM is to use an adaptive one-dimensional CNN to replace the fully connected layers of the network. The size of the convolutional kernel of the 1D CNN is k, which represents the coverage of the channel interactions and is proportional to the size of the channel dimension, C, so k can be adaptively determined by equation (2), in which odd denotes that the value of k is an odd number.

$$k=\psi(C)=\left|\frac{\log_2(C)}{\gamma}+\frac{b}{\gamma}\right|_{odd} \qquad (2)$$

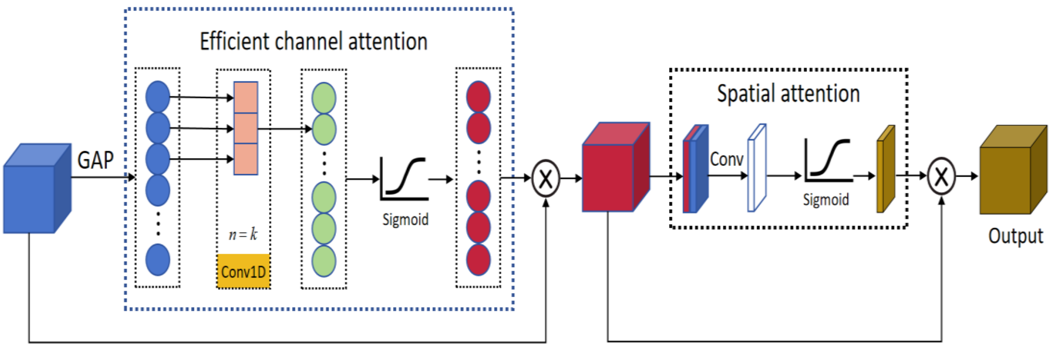

Figure 5: Schematic diagram of the attention module in this paper

The attention mechanism in GhostNet (Wang & Li, 2022) only focuses on the information in the channel dimension, and lacks attention to the spatial dimension, which is one of the keys to identify effective regions in the feature map. Therefore, spatial attention is also included in the attention module of this paper. Spatial attention mainly consists of pooling and convolution operations, which can perform maximum and average pooling operations on spatial features, and convolve the two results to obtain the attention weights. In general, LHAM adopts adaptive one-dimensional CNN, which greatly reduces the number of network parameters.

At the same time, LHAM can also effectively extract the spatial dimension of attention without generating a large number of parameters, which improves the accuracy of the network. Compared with the existing attention methods, the attention module proposed in this paper realizes a good balance between effectiveness and lightweight, and further improves the performance of the network.

2.3 Model performance validation experiments

In this paper, a large number of experiments are conducted on the publicly available GAIT-IST dataset to prove the superiority of the model in this paper, and the effectiveness of the proposed attention module is demonstrated by the ablation experiments. The performance and parameter comparisons between this model and other models are shown in Table 1.

Table 1: Accuracy and number of model parameters for the gait dataset

DATASET	METHOD	NO. OF PARTICIPANTS (MILLIONS)	ACCURACY(%)
GAIT-IST	Fine-tuning VGG-19	139	96.89
	MobileNetV3	4.1	95.88
	GhostNet	4.2	96.47
	Our model	2.6	98.24

To verify the validity of the attention mechanism, ablation experiments were conducted in this paper, and the results can be found in Table 2.

Table 2: Ablation experiments with different attention modules

DATASET	ATTENTION MODULES	NO. OF PARTICIPANTS (MILLIONS)	ACCURACY(%)
GAIT-IST	SE module	4.1	97.08
	CBAM	4.1	98.11
	Our module	2.6	98.14

The experimental results show that the model in this paper can accurately recognize the gait information of athletes and provide data support for the study of overuse injuries in athletes.

3. Overuse injury detection in good distance runners

3.1 Overuse injury studies in distance runners

Long-distance runners due to its project technical characteristics of the lower limb large muscle groups for a long time alternating continuous movement, resulting in the overuse of the lower limbs, high incidence of sports injuries. Middle-distance running training belongs to the endurance physical dominance category of projects, is a lower limb constantly alternating periodic movement (Furrer, Hawley, & Handschin, 2023), physical dominance of the characteristics of the middle-distance runners, so that the training of middle-distance runners is mainly based on endurance speed as the core of the physical quality of the development. Good athletes can train more than 35 hours per week before winning a major championship (Haugen, Sandbakk, Enoksen, Seiler, & Tønnessen, 2021). High-intensity training and multiple competition programs can put tremendous stress on the athlete's body. When these repetitive loads result in too much stress or too little recovery time between training sessions, overuse injuries will occur, with musculoskeletal injuries being the most common. The injury sites are mainly focused on lower limb injuries, with patellofemoral pain, iliotibial bundle syndrome, medial tibial stress syndrome, Achilles tendon injuries and plantar fasciitis being common sports injuries in middle and long-distance runners.

The training variables most frequently associated with overuse running injuries are running frequency, duration, distance and speed (Prakash, Kumar, & Mittal, 2018), with over 60% of running injuries attributable to training errors. However, it has been suggested that injured athletes train as intensely as other runners for as long a period of time before suffering an overuse injury, and that for most overuse injuries there are also underlying anatomical or biomechanical features that make them more susceptible to injury. One study alone attributed factors associated with running injuries to lack of strength (Gholami, Napier, & Menon, 2020), clubfoot, reduced muscle flexibility, reduced vertical jump height, prolonged reflex reaction time , and poor balance. In addition, there are lower limb hypoplasia, limited flexibility (Ahmadi et al., 2014), weak core muscle endurance, and knee valgus. It has been suggested that 40% of running injuries are related to biomechanical errors and that there is a correlation between gait abnormalities and injuries. Most of these intrinsic influences on injury can find their counterparts in the structural elements of the body's motor function in the function of the joints, the function of the muscles and the further subdivided elements of the motor function. In terms of the type of injury (overuse vs. traumatic), approximately 50-75% of sports injuries may be due to the constant repetition of the same movement. It has also been shown that the endurance group (76%) had a higher incidence of overuse than the whole team (48%), with the majority of injuries (79%) occurring in the lower extremities, and 88% of cases being training related. The most common site of injury in these injuries was the leg, with the most vulnerable areas being the knee and calf (Chan et al., 2018). Common running injury symptoms include patellofemoral pain, iliotibial bundle syndrome, medial tibial stress syndrome, Achilles tendon injuries, and plantar fasciitis (Paquette, Napier, Willy, & Stellingwerff, 2020). Most sports injuries can be categorized as "overuse" injuries, which occur when there is an imbalance between the repetitive loading of tissues and their adaptive capacity. In China, Zhu Linlin investigated the injuries of 37 athletes from a sports academy specializing in middle and long-distance running, and found that chronic injuries predominated in the students, accounting for 59.4% of the number of investigations, and acute injuries accounted for 40.6%. The injury rate of running is high, and the injury site is mostly chronic injury of the lower limbs, and most of the sports injuries can be categorized as "overuse" injuries.

3.2 Studies related to the influence of gait parameters on sports injuries

The relationship between the ratio of a single-step support time to the vacated time is directly related to the size of the step length . Blindly emphasizing on increasing the stride length will lead to longer single-step vacating time of the athlete, and the duration of the single stride will be lengthened accordingly. The running gait parameters most closely related to injury are excessive stride length and bouncing. Studies have shown that stride frequency is lower in the population of cross-country runners who develop tibial injuries . When the initial contact of the foot is further from the front of the body, the braking impulse of the leg increases, thereby increasing the force absorbed by the lower leg. As a result, over-striding is usually associated with stress damage to the lower leg tibia .

Reducing impact forces can be accomplished with a higher stride frequency, a forward whipping pattern, and an increased forward lean angle as a way to limit impact forces and reduce the risk of knee pain and tibial stress fractures. It has also been suggested that there is no significant difference in stride frequency for novice runners who experience anterior knee pain and any RRI compared to the healthy population (Wade, Needham, McGuigan, & Bilzon, 2022). As running speed increases, the runner's gait changes to adapt to the change in speed, and one of the most noticeable changes in gait is the change in foot landing pattern from the hindfoot to the forefoot, which shortens the gait cycle and increases running speed. However, when runners run at top speed for extended periods of time, their mechanical systems break down and a number of gait characteristics that increase the risk of injury become apparent. It has been suggested that male novice runners have shorter ground contact times and that there is a higher left-right side asymmetry in ground contact times in male runners with RRIs (Davis & Futrell, 2016). It can be seen that gait is associated with sports injuries in middle-distance runners, and that too large a stride or low stride frequency increases the stress absorbed by the lower leg, which may trigger an injury.

3.3 Gait information collection of excellent long-distance running athletes

In this paper, a video camera was used to collect gait information of excellent long-distance runners running on the way after full warm-up, to collect gait parameters of athletes with different injury histories, and finally to analyze and compare the gait parameters mathematically.

3.3.1 Test equipment and site layout

In order to simplify the experimental equipment so as to expand the scope of application of the experimental results, this paper uses a high-speed camera acquisition system (TSLE250) placed on the side of the runway at a distance of about 15 meters from the plane of motion, with a shooting height of 1.1 m, a shooting range of 3 to 4 meters, and 1 to 1.5 repetitions of the cycle of steps. The shooting speed was set to 60 frames/sec, 5x exposure, and the shutter speed was set to 0.0042 s. The site layout is shown in Figure 6.

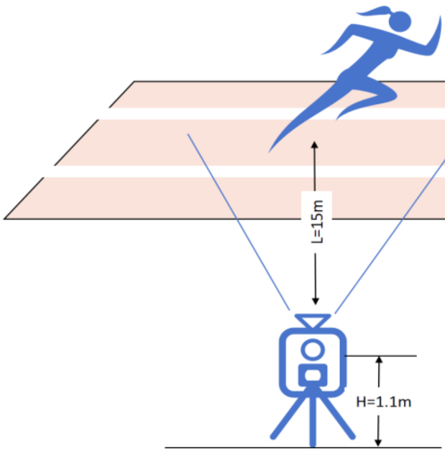

Figure 6: Test site layout

3.4 Detection effect of the detection model on different damage sites

As shown in table 3,comparison of the four time phases of ankle joint angle (left foot on ground, left foot off ground, right foot on ground and right foot off ground) between outstanding athletes with and without previous ankle injury due to overuse showed that the ankle joint angle of athletes with no history of ankle injury was greater in the left foot off ground and right foot off ground than that of the athletes with a history of injury and the difference was highly significant ($p<0.01$) and significantly different ($p<0.05$), while the ankle angle of all athletes in the left foot on ground and right foot off ground was greater than that of the athletes with a history of injury, the difference was highly significant (p<0.05). highly significant (p<0.01) and significant (p<0.05), while there was no significant change in the ankle angle of all athletes at the moment of landing of the left foot and the moment of landing of the right foot.

Table 3: Comparison of Subjects' Ankle Angles

GAIT PHASE	ANKLE ANGLE		T	P
	NON-INVASIVE EXPERIENCE	EXPERIENCED WITH INJURY		
LEFT FOOT STRIKE	123.43±14.31	126.08±11.46	0.626	0.547
LEFT FOOT OFF GROUND	114.89± 11.47	99.30 ± 8.74	3.895	0.004 ◎◎
RIGHT FOOT STRIKE	107.42±8.05	104.27±7.94	0.96	0.362
RIGHT FOOT OFF GROUND	127.17 ± 7.54	118.83± 9.37	2.705	0.024 ◎

*(**Note:** ◎ Comparison of ankle angles on the same side before and after the 10-kilometer run, ◎ P<O.05, ◎ P<O.01)*

As shown in table 4, comparison of the four time phases of knee angles (left foot landing, left foot off the ground, right foot landing, and right foot off the ground) of outstanding athletes with and without knee injuries showed that the knee angles of athletes with no history of knee injuries were larger than those of athletes with a history of injuries at the time of landing and the time of off the ground, and the difference was significant (p<0.05). The difference was significant (p<0.05), while the knee angles of the athletes with no history of knee injury were greater than those of the athletes with a history of knee injury at both the moment of landing on the right foot and the moment of leaving the ground, and the difference was not significant (p>0.05).

Table 4: Comparison of Subjects' Knee Angles

GAIT PHASE	KNEE JOINT		T	P
	NON-INVASIVE EXPERIENCE	EXPERIENCED WITH INJURY		
LEFT FOOT STRIKE	254.18 ± 18.82	242.1± 16.51	2.443	0.037◎
LEFT FOOT OFF GROUND	237.28 ± 23.48	220.7± 17.03	2.371	0.042◎
RIGHT FOOT STRIKE	194.83±8.20	196.46±7.95	0.791	0.449
RIGHT FOOT OFF GROUND	203.77±20.70	204.41±20.70	0.238	0.817

*(**Note:** ◎ Comparison of ankle angles on the same side before and after the 10-kilometer run, ◎ P<O.05, ◎ P<O.01)*

As shown in table 5, comparison of the four time phases of the elbow joint angle of outstanding athletes with and without previous injury to the elbow joint caused by overuse showed that the elbow joint angle of athletes with no history of elbow joint injury at the moment of the left foot coming off the ground was greater than the shoulder joint angle of athletes with a history of elbow joint injury, and the elbow joint angle of the rest of the three time phases were smaller for athletes with no history of injury than for athletes with a history of injury, but only for athletes with a history of injury on the right side of the elbow. The change in elbow angle between the moment of foot landing and the moment of leaving the ground was significant (p>0.05).

Table 5: Comparison of Subjects' Elbow Angles

GAIT PHASE	ELBOW JOINT		T	P
	NON-INVASIVE EXPERIENCE	EXPERIENCED WITH INJURY		
LEFT FOOT STRIKE	96.36±17.57	100.25±13.86	0.848	0.418
LEFT FOOT OFF GROUND	89.77±11.07	85.33±15.85	1.571	0.151
RIGHT FOOT STRIKE	85.82 ± 11.07	95.27 ± 16.40	2.544	0.031◎
RIGHT FOOT OFF GROUND	76.11 ± 21.38	93.37 ± 26.14	2.822	0.02◎

*(**Note:** ◎ Comparison of ankle angles on the same side before and after the 10-kilometer run, ◎ P<O.05, ◎ P<O.01)*

4. Conclusion

Excellent long-distance runners have honed their strong will and excellent sports character due to long-term training, and are able to overcome various difficulties in training. However, the accumulated injury symptoms caused by overuse due to long-term high-intensity training are not significant at the beginning stage, so they are easy to be ignored by athletes, and only when the overuse injury accumulates to a certain degree affecting normal training will they be found by athletes, which directly affects the athletes' sports level and training level.

Based on deep learning technology, this paper studies the gait of excellent long-distance runners, constructs an overuse injury detection model, and proves through experiments that the experimental detection effect has a high degree of accuracy.

It provides a proven detection method for long-distance runners to discover the overuse state early and avoid injury. At the same time, it is also an intentional practice of the deep integration of deep learning technology and sports practice, which points out the direction for sports research using deep learning technology.

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