Deep Neural Network-based Injury Prevention Modeling for Non-contact Track and Field Training

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ABSTRACT. *Non-contact training injuries may lead to a decrease in the training level of track and field athletes, so the effective prevention of training injuries is of great importance to the healthy growth of track and field sports. In this article, a deep neural network-based non-contact track and field training injury prevention model is constructed to address the issues of large error and low efficiency of the prediction results of current methods. Firstly, the anti-saturation transformation module is introduced to optimize the GRU (EGRU) and dwindle the complexity of the model. Secondly, the influencing factors of non-contact track and field training injury are selected and preprocessed, and then the influencing factors are decomposed into a series of eigenmode function components using Empirical Modal Decomposition (EMD), and the optimal centers of each modal IMF component are adaptively matched using a recursive solving method to achieve the purpose of data dimensionality reduction. Finally, causal convolution is used to focus the local temporal features of the IMF sequence in the longitudinal direction in advance, and the features obtained from the convolution are serialized and modeled using EGRU to complete the prediction of damage types. The experimental outcome implies that the constructed model has a MAE of 0.046, a MAPE of 0.1393, a RMSE of 0.0572, a co-efficient of determination of 0.9812, and a prediction time of only 0.15 s. Compared with the comparative models, the prediction speed is faster and the prediction accuracy is higher, which provides a basis for the prevention of non-contact track and field training injuries.*
Keywords: Injury prevention; Deep neural network; GRU; Empirical modal decomposition; Causal convolution.

1. **Introduction.** As the "mother of all sports", track and field occupy a significant position in competitive sports, and its strength is a significant symbol of a country's competitive sports level [1]. Domestic and international studies have reported that irrational training load arrangement is an important reason for the high incidence of non-contact

track and field training injuries [2, 3]. Reasonable training loads can induce benign adaptations in the organism, but on the contrary, it may negatively affect the adaptive process of athletes, resulting in poor athletic performance, psychological problems, and even diseases or injuries. How to minimize and delay the occurrence of injuries and illnesses, and how to maximize the duration of optimal athletic performance is an urgent challenge in the current track and field training and competition process [4, 5]. With the development of artificial intelligence technology such as big data analysis, machine learning, deep learning, etc., relying on artificial intelligence technology to build an intelligent prevention model of sports injury is a very meaningful work in the field of track and field training [6].

1.1. **Related work.** Galambos et al. [7] found that injured track and field athletes recorded a higher training volume in a single event in the week prior to injury than non-injured athletes, so they proposed a prediction theory based on the risk of sports injuries. Claudino et al. [8] proposed a Random Forest-based injury risk prevention model based on the technical and tactical statistics of track and field athletes. Ellis et al. [9] proposed a non-contact track and field training injury risk early warning model based on the quantitative GPS data, and applied the time sliding window technique and linear support vector machine for feature reconstruction and feature selection, respectively. Mohr et al. [10] collected track and field training loads and sports injury data, used principal component analysis for dimensionality reduction, and chose logistic regression and support vector machine for modeling of sports injuries. Rossi et al. [11] proposed a model based on GPS external load monitoring and machine learning algorithm for multidimensional prediction of training injuries in track and field, using ADASYN to address the data imbalance issue. Colby et al. [12] monitored the training load, skeletal muscle screening and subjective perceived health data of track and field athletes, thinking that the lower limb The results of univariate analysis were incorporated into the model construction of multivariate generalized estimating equations for the dependent variable of non-contact injuries. López-Valenciano et al. [13] proposed a muscle injury risk prevention model based on the SmoteBagging algorithm, but the prediction efficiency was not high. Ayala et al. [14] measured individual characteristics, psychological factors, and neuromuscular factors of track and field athletes, and constructed a prediction model for lower extremity hamstring non-contact injury risk based on the SmoteBoostM1 algorithm, which enhanced the prediction efficiency.

Artificial neural networks, with good robustness and adaptive properties, have been widely used in sports injury prediction [15]. Falamarzi et al. [16] established a risk prediction model for non-contact track and field training injuries by using a multilayered perceptual neural network. Yang et al. [17] used gender, injury history, lower extremity YBT test, and FMS test as independent variables to predict the risk of non-contact injuries using a BP neural network, but the prediction accuracy was not high. Chen et al. [18] predicted non-contact track and field training injuries based on the collected track and field injury causative factors using BP neural network, but the prediction accuracy was not high. As feedforward neural networks such as BP and RBF are prone to overfitting for small-scale data, CNN and RNN deep neural networks perform better in classification and prediction of complex tasks. Song et al. [19] analyzed the effects of exercise fatigue, exercise load, and competition weather on the rate of sports injuries, and used the influencing factors as inputs to CNNs for track and field training injury prevention. Alghamdi [20] summarized the factors affecting track and field training injuries and predicted them using RNN.

1.2. **Contribution.** In summary, when scholars use machine learning or feed-forward neural networks for non-contact track and field training injury prevention, the prediction accuracy of the models is generally not high. To deal with the above issues, this article constructs a deep neural network-based injury prevention model for non-contact track and field training. Firstly, to alleviate the "gradient explosion" problem of traditional GRU, the anti-saturation transformation module is introduced to optimize GRU (EGRU). Second, the influencing factors of non-contact track and field training injuries were selected based on the existing research, and the influencing factors were pre-processed using the normalization method. Then the influence factors are decomposed into a series of intrinsic modal function components using Empirical Modal Decomposition (EMD), and the optimal center of each modal IMF component is adaptively matched using a recursive solution method to improve the non-stationarity of the data. Finally, based on causal convolution and EGRU, the optimal IMF component sequences decomposed above are subjected to double feature extraction and double data filtering to output the prediction results of damage types.

2. **Related theoretical analysis.**

2.1. **Neural Networks for Gated Recurrent Units.** LSTM is adopted to analyze time series data and solves the problem of gradient explosion and gradient vanishing in RNN processing long period data [21]. GRU is a deep RNN that improves the structure of LSTM [22]. The difference in prediction accuracy between the two is not significant, but the GRU model has fast convergence speed and low running cost. The reset gate is responsible for combining the current input information with the past information, and the update gate saves the memory information by setting the time step. The framework of GRU neural network is implied in Figure 1.
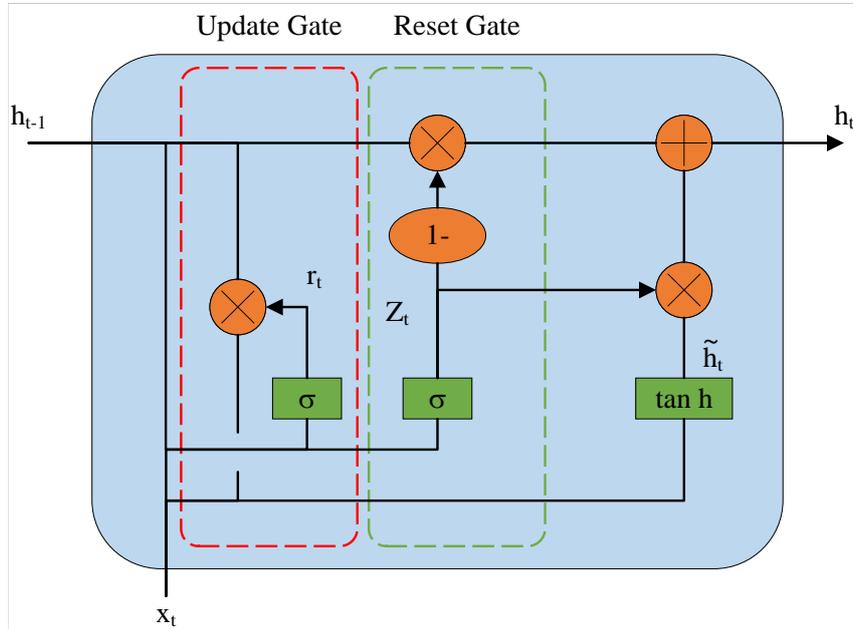

Figure 1. The framework of GRU neural network

$$z_t = \sigma(V^{(z)}x_t + W^{(z)}g_{t-1}) \tag{1}$$

$$r_t = \sigma(V^{(r)}x_t + W^{(r)}g_{t-1}) \tag{2}$$

$$\tilde{g}_t = \tanh(r_t W g_{t-1} + V x_t) \tag{3}$$

$$g_t = (1 - z_t)\tilde{g}_t + z_t g_{t-1} \tag{4}$$

where z_t is the update gate; r_t is the reset gate; r is the hidden layer input; $\tilde{g}_t$ is the aggregation of input x_t and the past hidden layer state g_{t-1}; $V^{(z)}, W^{(z)}, V^{(r)}, W^{(r)}, V, W$ are the trainable parameter matrices; tanh is the activation operation.

2.2. **Causal convolution.** Causal convolution is used by spatio-temporal convolutional networks (TCNs) to ensure a unique correlation between the current time step and its historical sequence [23], as indicated in Figure 2.
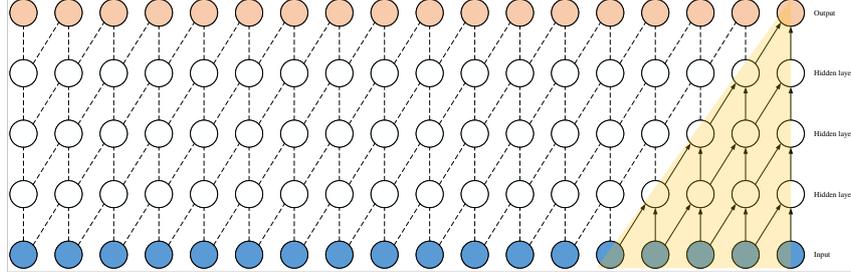

Figure 2. The structure of causal convolution

The causal convolutional structure allows the network to make predictions only from past information, which meets the causality requirement of time series modeling, and the unidirectional structure of causal convolution reduces the interference of future input data in the computation because the network can only use the historical data that has already been observed in the prediction, which helps to avoid the interference of future information in the prediction, and thus improves the speed of convergence of the model learning and the accuracy of the network output. This helps to avoid the interference of future information in the prediction, thus improving the convergence speed of model learning and the accuracy of network output.

3. **Improvements of GRU.** The traditional GRU is with the issues of "gradient vanishing" and "gradient explosion". For the goal of improving the forecasting accuracy of the model and alleviate the problem of "gradient vanishing", this article suggests an improved GRU (EGRU), which introduces an anti-saturation transformation module Tri, to make the GRU more sensitive to the learning of data features and reduce the complexity of the model.

For the purpose of enhancing the model learning's sensitivity, EGCU introduces the anti-saturation transition function Tri, and EGCU adopts the whole data flow message c_{t-1} up to the former moment of the "reprovision gate" computation process.

The "reset gate" h_t decides the amount of the former moment's data is able to be preserved until the recent moment, where x_t is the t-th ingredient of the sequence x, and x_t is exponentially transformed by multiplying it with the weight matrix V. g_{t-1} holds the data from the $t-1$ time, and is linearly transformed by amplifying it with V. The data information's two portions are attached together and then computed through δ function, δ is the Sigmoid activated operation, so that the numerical outcome h_t is among (0,1), as indicated in Equation (5).

$$h_t = \delta(V_{hg}g_{t-1} + V_{hx}x_t + b_h) \tag{5}$$

To improve the learning ability of the "update gate" i_t on historical data, the "update gate" i_t of EGRU adopts the entire data flow message up to the previous moment c_{t-1}. The "reset gate" of EGRU adopts the Sigmoid activated operation, and when the initial data

comes into the "saturation zone" of the "reset gate", the value will change easily, leading to the sensitivity of studying reduced. The calculation of i_t is indicated in Equation (6).

$$i_t = \delta(V_{ig}g_{t-1} + V_{ix}x_t + c_{t-1} + b_i) \tag{6}$$

For the purpose of enhancing the model learning's sensitivity, the anti-saturation conversion operation Tri is used into EGRU, when the data passes through the "reset gate", the output data of the "reset gate" will be converted by the conversion module Tri, as indicated in Equation (7).

$$Tri = \tanh(i_t) \tag{7}$$

c_t is the data message reserved from the starting to the recent moment, as implied in Equation (8).

$$c_t = g_t c_{t-1} + Tri \tag{8}$$

where g_t is the data information reserved at the current moment. c_t through the tanh function to control the current moment how much data message can be reserved until the next moment, as indicated in Equation (9).

$$g_t = \tanh(c_t) \tag{9}$$

The gradient calculation of EGRU is implied in Equation (6), with the accumulation of historical data, x is usually greater than 0. Where $y = V_{ig}g_{t-1} + V_{ix}x_t + c_{t-1} + b_i$, with the accumulation of historical data y is usually greater than 0, the range of values of operation gradient z will be more sensible. Thus, this model can excellently facilitate the problems of "gradient disappearance".

4. Deep neural network-based injury prevention modeling for non-contact track and field training.

4.1. Selection of Injury Causing Factors and Pretreatment of Non-Contact Athletic Training Injuries.
To enhance the prediction efficiency of traditional models, this article designs a deep neural network-based injury prevention model for non-contact track and field training injuries, as indicated in Figure 3. Firstly, the injury-causing factors of non-contact track and field training injuries are selected based on existing studies and normalized, secondly, the injury-causing factors are decomposed into a series of intrinsic modal function components using EMD algorithm [24], and the optimal center of each modal component is adaptively matched using a recursive solving method. Finally, the causal convolution is used to focus the local temporal features in the longitudinal direction of the modal sequence in advance, and the features obtained from the convolution are serialized and modeled using a gating mechanism to output the prediction type of the injury.

The occurrence of non-contact athletic training injuries is usually the outcome of a combination of factors. To make a more precise prevention of the occurrence of training injuries, it is first essential to study clearly what factors can directly or indirectly lead to the occurrence of athletic injuries. On the basis of existing research [25], it can be concluded that are based on personal basic information, training load, subjective perception of health, sports quality and history of injury records of the six aspects of injury-causing factors selection, to derive the indicators of its influence factors: age, height, BMI, years of training, short-term cumulative load, long-term cumulative load, quality of sleep, muscle aches and pains, stress levels, and other 50 indicators of the impact, which are recorded as: $X = \{x_1, x_2, \ldots, x_{50}\}$, as the input data of the forecasting model, and the types of
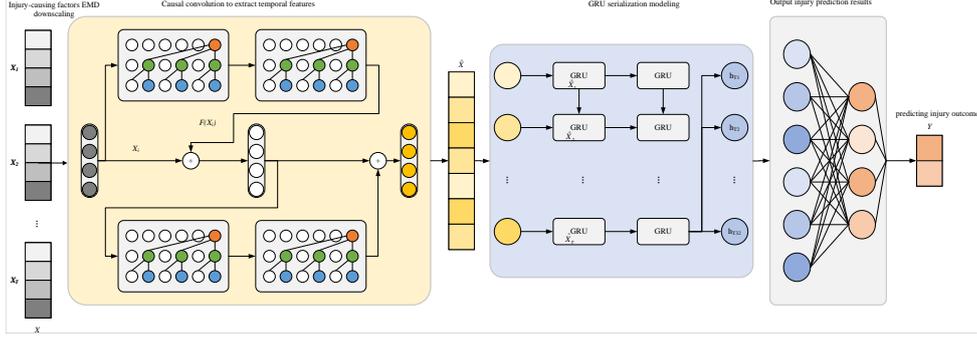
Figure 3. The suggested model of non-contact track and field training injuries

track and field training injuries (strain injuries, fracture injuries, self-damage injuries and breakage injuries, etc.) as the output variables of the prediction model, denoted as Y.

To eliminate the influence of the scale and magnitude of the injury factor data on the prevention model, the normalization method is usually adopted, which makes the model converge faster and reduces the computational complexity at the same time. Normalization compresses the data to [0,1].

$$x^* = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

where x^* represents the data obtained after normalization of the original data, x represents the injury factor to be normalized, $x_{\min}$ represents the minimum value in the data, and $x_{\max}$ represents the maximum value in the data.

4.2. **Empirical modal decomposition of factors influencing non-contact track and field training injuries.** Due to the large number of factors affecting track and field training injuries, this paper uses empirical modal decomposition EMD to decompose the 50 injury-causing factors into a series of intrinsic modal function components, and uses a recursive solution method to adaptively match the optimal center of each modal component to obtain the purpose of data degradation and enhance the non-stationarity of the data. The steps in detail are as follows:

(1) For the injury-causing factor $x(t)$, find out all the extreme values and minima within its range, and then use the interpolation method to connect the extreme values and minima to form an envelope, and at the same time find out the mean value $a_1(t)$ of the envelope of the extreme values and minima and connect it to the curve.

(2) $x(t)$ subtracts the envelope mean $a_1(t)$ to obtain a preliminary intrinsic modal function $h_1(t)$. $h_1(t)$ is analyzed to see if it satisfies the two requirements for an IMF subcomponent, and if it does, the component is treated as an intrinsic modal function, i.e., $c_1(t) = h_1(t)$.

(3) If the two requirements of the IMF subcomponents are not satisfied, make $x(t) = h_1(t)$, recalculate step (1) with k iterations, and compute the central real-valued function $w(t)$ associated with $h_1(t)$ after putting $h_1(t)$ through the Hilbert transform [26] to create the following objective function.

$$\min_{\{h_k\},\{w_k\}} \left\{ \sum_k \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * h_k(t) \right] e^{-jw_k t} \right\|_2^2 \right\} \tag{11}$$

where $\delta(t)$ is a singular function.

The constrained variational issue is turned into an unconstrained variational issue by adopting the Lagrange factor μ and the quadratic penalty term β. The updating of h_k, w_k

and μ is realized by the alternating direction multiplier method, and the "saddle point" of the generalized Lagrange expression [27] is searched to find the optimal solution of the constrained issue.

The modal components are iterated to find the optimal solution by initializing h_k, w_k, and μ. When all $w \geqslant 0$, h_k and w_k are updated according to the EMD algorithm formulation, and the Lagrange multiplier μ is double boosted until the iteration constraints are satisfied and the iteration is stopped.

$$
\begin{cases}
\displaystyle\sum_{k=1}^{K} \frac{\|h_k^{n+1}(t) - h_k^n(t)\|_2^2}{\|h_k^n(t)\|_2^2} < \zeta_r \\
\displaystyle\sum_{k=1}^{K} \|h_k^{n+1}(t) - h_k^n(t)\|_2^2 < \zeta_a
\end{cases}
\tag{12}
$$

where ζ_r and ζ_a refer to relative and absolute tolerances.

(4) Subtract $x(t)$ from the IMF1 component $c_1(t)$ to obtain the remaining component $r_1(t)$, the residual.

Up to this point, an intrinsic modal function component IMF1 and a residual $r_1(t)$, and then let $x(t) = r_1(t)$. Repeat all the above steps, and the iteration stops when $r_1(t)$ becomes monotone data. $x(t)$ is decomposed into an optimal IMF component and a residual component.

$$
x(t) = \sum_{i=1}^{q} c_i(t) + r_q(t)
\tag{13}
$$

where $0 < q < 50$.

4.3. Deep neural network-based injury prevention for non-contact track and field training.

To enhance the efficiency of prevention, in this paper, based on causal convolution and improved gated recurrent neural network (EGRU), the optimal IMF component sequences decomposed above are subjected to double feature extraction and double data filtering, and then the damage types are predicted by EGRU as follows.

For the input IMF sequence X_i, the features are extracted by causal convolution, i.e., the sliding convolution kernel $F = (f_1, f_2, \ldots, f_K)$ (f_k is the weight at the position, $k = 1, 2, \ldots, K$ and K are the size of the convolution kernel) is convolved with different parts of the input sequence, and the resulting convolution values are as follow:

$$
F(X_i) = \sum_{k=1}^{K} f_k X_{i-(K-k)d}
\tag{14}
$$

where d is the dilation factor, when $d = 1$, the causal convolution operation is performed on the input data, and when $d \neq 1$, the dilation causal convolution operation is performed on the input data.

Adding residual connections to causal convolution to better capture long-term dependencies in sequences.

$$
o_i = \sigma(F(X_i) + X_i)
\tag{15}
$$

where $\sigma(\cdot)$ is the ReLU activation function.

After the causal convolution layer is convolved, the feature sequence is $\hat{X} = (\hat{X}_1, \hat{X}_2, \ldots, \hat{X}_T)$, and the EGRU is used to predict the non-contact track and field training injuries, which mainly makes up of a reset gate and an update gate, the reset gate determines the degree

of integration between the previous moment and the current input, and the update gate determines the degree of retention of the previous moment state information in the current moment. As the input to the EGRU neural network, the input of the EGRU unit at time step t is $\hat{X}_t$, and the output is g_t.

First, the splicing matrix of the current moment input $\hat{X}_t$ and the obscured state of the former moment is inputted into the EGRU unit to obtain the reset gate state r_t and update gate state u_t at time t.

$$r_t = \delta(V_r[g_{t-1}, \hat{X}_t] + b_r) \tag{16}$$

$$u_t = \delta(V_u[g_{t-1}, \hat{X}_t] + b_u) \tag{17}$$

$$\delta(p) = \frac{1}{1 + \exp(-p)} \tag{18}$$

where $\delta(\cdot)$ is the Sigmoid activation function, V_r, V_u are the weight matrices of the reset gate and the update gate respectively, $[\ ]$ is the symbol of the vector splicing operation, b_r, b_u are the bias vectors of the reset gate and the update gate respectively, and p is the independent variable of the activation function.

The reset gate then selectively resets g_{t-1} to determine how much of the previous moment's information has been retained. g_{t-1} is added to the reset gate and the tanh activation function is applied to obtain the current candidate state.

$$\tilde{g}_t = \varphi(V_g[r_t \odot g_{t-1}, \hat{X}_t] + b_g) \tag{19}$$

$$\varphi(p) = \frac{\exp(p) - \exp(-p)}{\exp(p) + \exp(-p)} \tag{20}$$

where $\varphi(\cdot)$ is the tanh activation function, V_g is the weight matrix of the candidate state, $\odot$ is the element-by-element multiplication symbol, and b_g is the corresponding bias vector.

Finally, the EGRU unit combines and processes the current moment information, and processes the historical moment information in combination with $I - u_t$ (I is the unit matrix) and the anti-saturation conversion module Tri, which are added together to obtain the output of the EGRU unit at the current moment.

$$g_t = (I - u_t) \odot g_{t-1} + \tanh(c_t) \tag{21}$$

where $c_t = g_t c_{t-1} + Tri$ is the data message reserved from the beginning to the recent moment.

The EGRU is able to efficiently capture key information in long-term sequences. At each moment, the EGRU dynamically retains and updates the related information and passes it on to the next time step of the network until the model has processed the entire sequence. The obscured state at the last time step is passed as an input to the fully connected level, which is linearly mapped to produce the final prediction of non-contact athletic training injuries.

5. **Performance testing and analysis.**

5.1. **Comparison and analysis of model prediction accuracy.** For the purpose of evaluating the deep neural network-based injury prevention model for non-contact track and field training, this article uses the training and exercise data of a school's track and field program collected in the literature [28] as a dataset, which contains the training records of 1,392 participants, the aspect of the exercise load, the body metabolism, and the condition of the body indexes. In this paper, the training data samples are divided into training set, testing set and validation set in the ratio of 6:3:1, and the forecasting results of PS-BP [17], EC-RBF [18], SP-CNN [19] and this paper's model FT-EGRU are compared and analyzed. The training accuracy of all models is 0.001, the learning rate is 0.01, the maximum number of iterations is 100, and the group length is 32. All the experiments are done in PythonV3.7 platform for programming, and Tensorflow2.0 framework to build the models.

To verify the advantages of the suggested model FT-EGRU in the prediction of non-contact track and field training injuries, different prediction models were trained in large quantities under the same dataset and then predicted on the test set, and four evaluation indexes, namely, MAE, MAPE, RMSE, and R^2 were adopted to judge the performance of the models.

The comparison of MAE of the four different models is indicated in Figure 4. The MAE of FT-EGRU model is the smallest, and the fluctuation of the error is smooth and basically stays in the range of 0.04-0.05. The MAE of PS-BP fluctuates the most, with a minimum of 0.095 and a maximum of 0.195, which indicates that the prediction performance of PS-BP is poor and unstable, and the fluctuation of EC-RBF is not as obvious as that of PS-BP, with a minimum of 0.09 and a maximum of 0.152. The SP-CNN performance is relatively smooth, basically keeping between 0.07 and 0.095, summarizing that FT-EGRU is more stable and reliable in prediction performance.
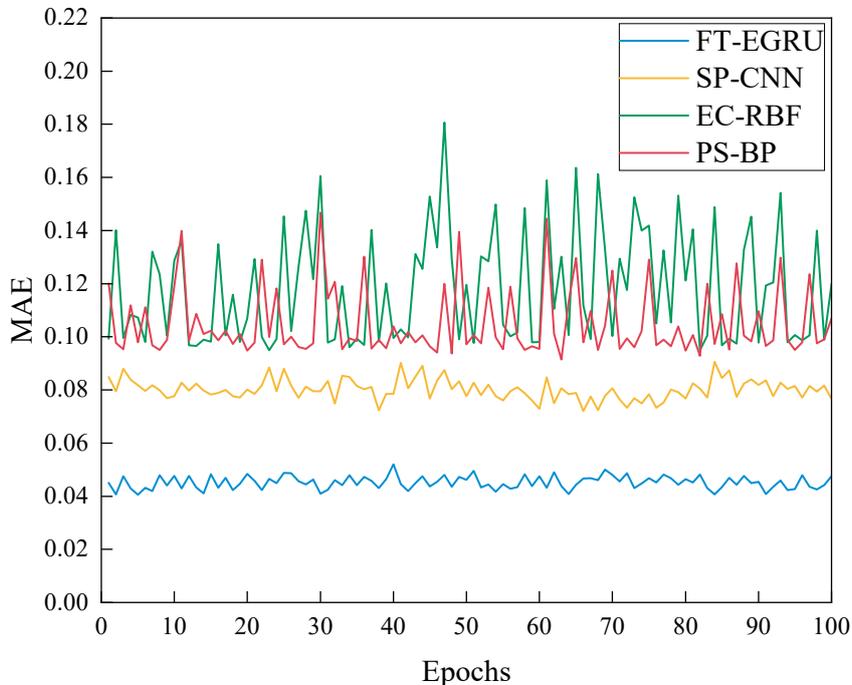

Figure 4. The comparison of MAE of the four different models

As can be seen from Table 1, the three indexes MAPE, RMSE and R^2 of FT-EGRU model are 0.1393, 0.0572, 0.9812 and 0.9409, respectively. Compared with PS-BP, EC-RBF and SP-CNN models, the MAPE of FT-EGRU decreased by 0.4746, 0.3369 and

0.1301. RMSE decreased by 0.1219, 0.0793 and 0.0242, both of which were the lowest among all prediction models. R^2 improved by 0.089, 0.0453, and 0.0185, the highest of all prediction models. This is because the PS-BP did not perform dimensionality reduction on the influencing factors, and the data redundancy is large, resulting in the worst prediction effect. The EC-RBF model directly inputs the collected injury-causing factors into the RBF for prediction, and the RBF has more parameters and a complex structure, so the prediction efficiency is not good. The SP-CNN model is based on the CNN to train the injury prediction, and the CNN is trained with more parameters compared to GRU training, and it does not screen the important injury-causing factors for features, so the prediction performance is lower than FT-EGRU. As a result, FT-EGRU is better than the other models in terms of prediction accuracy and model performance, which proves the effectiveness of FT-EGRU.

Table 1. Comparison of prediction accuracy of different models

Model	MAPE	RMSE	R^2
PS-BP	0.6139	0.1791	0.8922
EC-RBF	0.4762	0.1365	0.9359
SP-CNN	0.2694	0.0814	0.9627
FT-EGRU	0.1393	0.0572	0.9812

5.2. **Comparison of model's prediction accuracy and prediction time.** The comparison results of the four models, PS-BP, EC-RBF, SP-CNN and FT-EGRU, under different iterations are implied in Figure 5. As the number of training iterations increases, the prediction accuracy of all four prediction algorithms increases. Compared with the other three models, FT-EGRU has the fastest convergence speed, and the final converged accuracy is significantly higher than the other two models, in which the highest accuracy of FT-EGRU model in the validation set is 0.9829, PS-BP in the validation set is 0.8267, EC-RBF in the validation set is 0.8591, and SP-CNN in the validation set is 0.8902. The FT-EGRU is optimized for a simple structured GRU that captures the long-term dependencies of the sequence and introduces causal convolution to focus in advance on the local temporal characteristics of the longitudinal direction of the sequence, resulting in the highest prediction accuracy of the FT-EGRU model.

Comparison of the prediction time of different models is implied in Table 2, and the FT-EGRU model has a faster prediction speed, with a prediction time of only 0.15 s per prediction, which can satisfy the demand of injury prevention for non-contact track and field training. Compared with PS-BP, EC-RBF and SP-CNN models, the training time is reduced by 84.38%, 82.95% and 61.54%, respectively. PS-BP and EC-RBF models are based on feed-forward neural networks for training injury prediction, and the number of trained parameters is much higher than that of SP-CNN and FT-EGRU based on deep neural networks, resulting in longer prediction time. FT-EGRU not only reduces the parameters of GRU, but also decomposes the input data by EMD, so the prediction time is lower than that of SP-CNN.

Table 2. Comparison of prediction time of different models

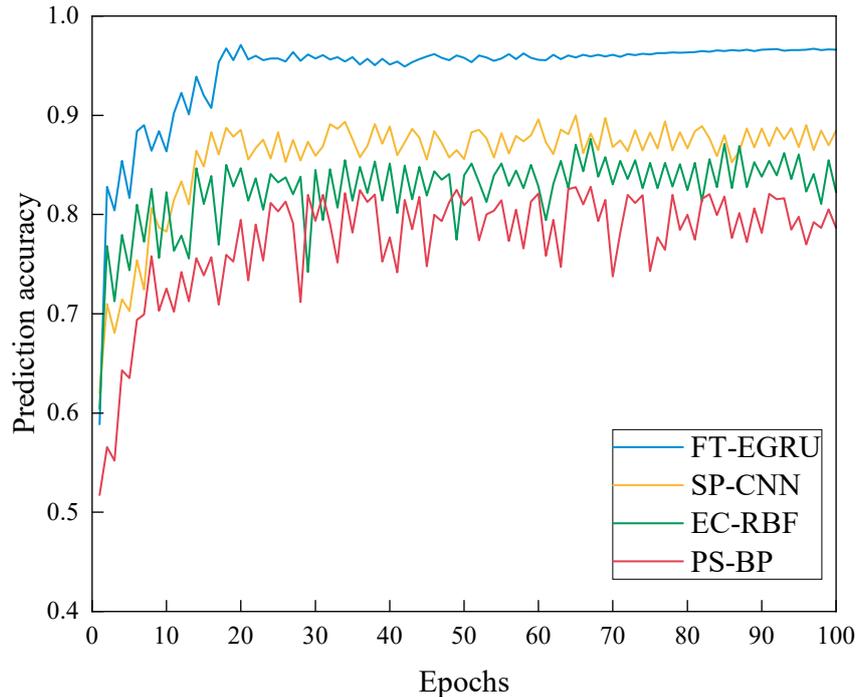| Model	PS-BP	EC-RBF	SP-CNN	FT-EGRU
Forecast time (s)	0.96	0.88	0.39	0.15

Figure 5. Comparison of prediction accuracy of different injury models

6. **Conclusion.** Prevention of non-contact track and field training injuries is of great value in improving the quality of track and field sports. In this article, a deep neural network-based non-contact track and field training injury prevention model is constructed to deal with the issue of poor prediction accuracy of current prevention models. Firstly, to alleviate the "gradient disappearance" problem of traditional GRU, the anti-saturation transformation module is introduced to EGRU. Secondly, based on the existing research, the influencing factors of non-contact track and field training injuries were selected and pre-processed using the normalization method. Then the influence factors are decomposed into a series of intrinsic modal function components using the EMD algorithm, and the optimal center of each modal IMF component is adaptively matched using a recursive solution method. Finally, based on causal convolution and EGRU, the decomposed sequence of optimal IMF components is subjected to double feature extraction and double data filtering, and serialized modeling is performed to output the prediction results of damage types. The experimental outcome implies that the proposed model effectively reduces MAE, MAPE, and RMSE, and can be better applied to non-contact track and field training injury prevention.

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