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ORIGINAL RESEARCH

Secure prediction and assessment of sports injuries using deep learning based convolutional neural network

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Abstract
In recent days, many information and image evidence in the field of medicine is being designed and developed by the advancement of computer technology. Presently, sport medical data is an essential department for medical sector and it is responsible for assuring sports safety based on the recovery level after an injury due to sports activity. The approach to reliably interpretation and valuable data information using a vast number of medical sports data and events has become an important research path in the collection and analysis of medical data. This paper discusses the extraction, study, and lack of training and accuracy of complex algorithms for critical sporting medical data. This paper involves with an optimized convolutional neural network (OCNN) based on deep-learning model to ensure successful detection and risk assessments of sport-medicine diseases and adopts the Self-Adjustment Resizing algorithm (SAR) augmented by the self-coding method of the convolution (SCM). CNN model helps to evaluate sports medicine in multi-dimensional results and suggested OCNN classification constitutes two convolutional layers, two pool layers, a fully connected layer, and a SoftMax structure that can be used for the classification of sport-related medical data. The CNN facilitates multi-dimensional sports medicine data analysis and to conclude a cloud-based loop model to create an advanced medical data network for sports medicine. Experiments illustrate that this approach offers technical support and guide to deploying a specific cloud-based fusion system.

Keywords Optimized convolutional neural network · Self-Adjustment Resizing algorithm · Self-coding method · Cloud-based loop model

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1 Outline of analysis of sports medical data using deep learning CNN

For deep learning, CNN is a deep neural network class which is most often used to examine visual imagery. Often noted for their common weight design and transfer invariance features, they are the change invariant (Wang et al. 2017) which provides image and video recognition tools, suggestion systems, image analysis, analyses of medical data, natural language processing, financial time series (Sato and Haegele 2017). An input and output stage, as well as several unknown layers, are part of a convolution neural network. Usually, the secret layers of a CNN consist of multiple convolution layers, combined with the propagation or a different point element. The activation function is usually layered and followed by additional convolutions such as ponds, fully connected layers, and normalization layers called hidden layers because the activation function and final convolution cover their inputs and outputs (Kooiman et al. 2017; Botelho et al. 2017) functions. Figure 1 illustrates the key principle

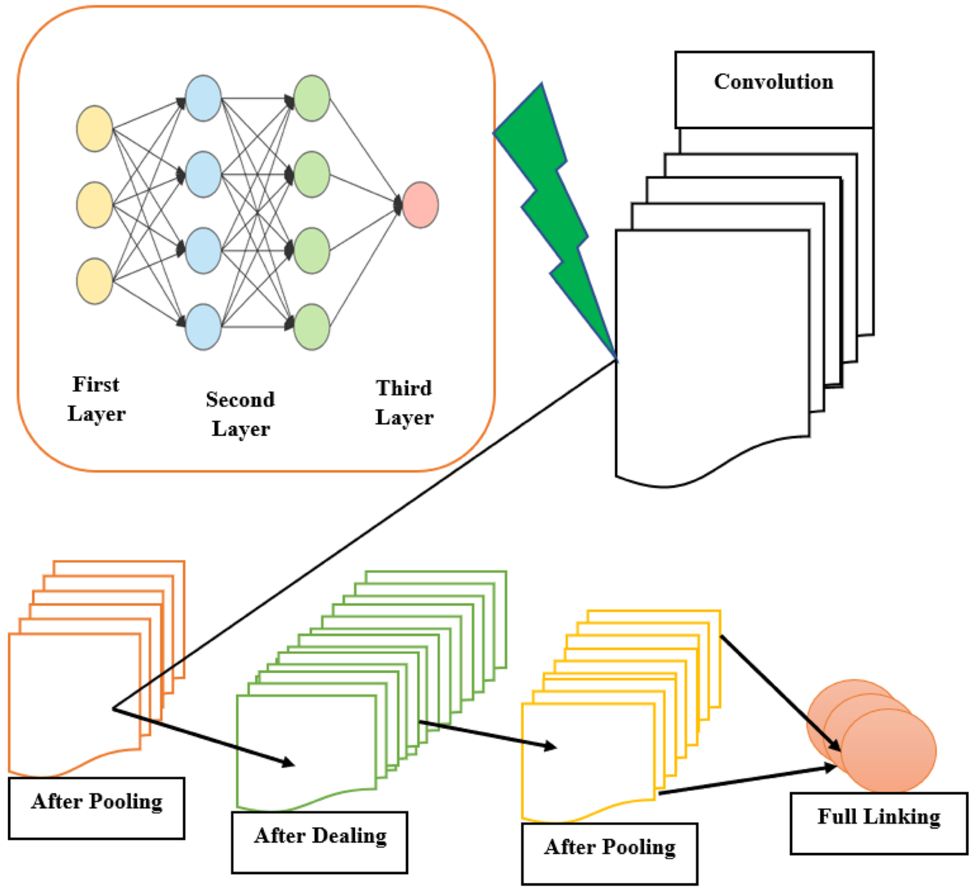

Fig. 1 Layer structure of deep learning CNN

of risk assessment and technology, which is the underlying technology direction in which the convolution neural network is coupled with large data (Rizk-Allah et al. 2019). Current networks may include local or global layers of pooling to reduce the underlying computation (Manogaran and Lopez 2018). Pool layers raising the data's measurements by integrating neuronal cluster production in the next layer into one neuron (Harasim 2017). Regional pooling is typically 2×2 tiny clusters, in which the comparison, pooling may measure peak or average. Global pooling works on all neurons of the convolution layer (Sato and Haegele 2018). Max pooling uses each of the neurons in the previous layer as its maximum value. Further, the average classification utilizes the average value of each neuronal cluster in the previous layer (Sato et al. 2017; Lo and Hew 2017).

Presently, many new technologies and research findings are focusing in the field of medicine and safety. The rapid development of IT and computer sciences are contributing to the production of a large volume of data in the medical sector, especially in sports injuries related data (Gebru et al. 2017; Hodge et al. 2017). The growth and advancement in sports medicine are largely focused on the study and evaluation of these results. The sports-related injury data is a category of complex information that contains a lot of details about sports-related injuries, sports-related diseases including multi-dimensional data (Lopez and Gunasekaran Manogaran 2017). In deep learning, a convolutional neural network is a multi-dimensional artificial intelligent (AI) algorithm (Spikol et al. 2018) has been analysed based on the assessment of the core details of large-scale health care data is an essential method for better analysis (Shakeel et al. 2018). The advancement of the Internet of Things allows the storing and retrieval of large data which is fast and efficiently analysed based on the sports medicine in real-time. Here, a huge number of medical sports details (Sudin et al. 2019), contains the CNN algorithm which loses the mode of training and the consistency of the algorithm has been evaluated based on mathematical formulation (Kirubakaran et al. 2020).

Therefore, it is important to create a computer cloud-based fusion platform to increase the effective prediction and risk assessment (Gomathi et al. 2019) in sports medicine. During the study and analysis of sports disease learning, sports medicine and the state of the things, several academics and research institutions focused on these issues (Nation-Grainger et al. 2017; Johnson et al. 2017). Concerning fundamental research, scientists proposed batch regularization, which suggested modifying, through expanding the level of training, the subsequent pattern of data of particular training (Lina and Zhihong 2017).

As a result, training issues and gradient uncertainty would rise and the diversified training results would be inferred using sports medicine's large data (Collins and Halverson 2018). The deep learning network algorithm suggests that it can realize hundreds of training levels and eliminates the full communication level which incorporates all functionality in a single module, so that faster data is available. In the same year, it is suggested that the creation and study through a completely sparse matrix training system of the representation details for sports medicine injuries, thereby rendering the associated horrible diseases a reality (Lakhani and Sundaram 2017).

2 Background study on deep learning convolution neural network (CNN) classification and its layers

In Calderón et al. (2017) it is identified that several successes in the identification of the body by a profound neural network model in traditional sports medicine is reported. Experiments show that the correct speed and accuracy of comprehension are above the medical standard which support a wide range of text instruction (Calderón et al. 2017).

To study broad data on sports medicine, in Merriam and Baumgartner (2019) authors discussed a common architecture for CNN (Merriam and Baumgartner 2019). The goal was to implement a model cyclic convolution, that realizes the actual data and develops machine effectiveness. The simple mining of huge sports medicine information is difficult and the expense to use and execute the algorithm is huge. The relief approach used for Naïve Bayas (NB), and the artificial neural network (ANN) classifiers has been selected by Margarito to classify all eight sports activities including riding, trainers, running, jumping, squatting, standing, walking, etc. (Capel et al. 2019). Under the ANN, authors in Brown et al. (2018) used the modified decision tree to categorize 9 sport activities comprising of sitting and standing in addition to lying down, jumping, biking, swimming, riding, Nordic football and spinning with a standard bicycle using the frequency domains obtained from the GPS and accelerometers (Merriam and Baumgartner 2020; Lowenthal and Snelson 2017; Martín-Gutiérrez et al. 2017). In Yoon and Armour (2017) authors proposed a sequential minimum optimization algorithm (SMO) for the seven sports activities utilizing mobile accelerometers measurements, with discrete wavelet transform (DVT)-based support vector machines (SVMs) (Bailon et al. 2019).

Deng et al. (2018) the low limb injuries are some of the most frequent and severe injuries among sporting practitioners, particularly those connected with knee joint. Therefore, an increased interest has developed over recent years in the identification of subjects with a high risk of injury. The measurement of the joint angles during dynamic motion is one of the most common injury risk factors. Techniques like human motion capturing and video analysis were commonly used for this purpose.

Gang et al. (2020) blood lactic acid development in exercise will fatigue the body and impair regular body activity. Therefore, the Chinese herbal compound mechanism for skeletal muscle exercise mediated injury has been extensively studied and explored from aspects of energy metabolism, mechanical damage, inflammation, free radicals and lipid peroxidation and growth factors that regulate repair of skeletal muscle damage. One or two of the seven Chinese herbal prescriptions which have good effects on muscle injury induced by exercise will be selected to provide theoretical bases for sports training, public health and labour hygiene.

Based on the statistical analysis, this paper analyses and explores the fundamental learning process and detailed research on sports medicine. Most of the issues must be overcome the problem of missing the training modes by the conventional deep learning algorithm. This paper suggests an in-loop fusion model for practical execution. The system provides technical support and helps that broad data in sports medicine are correctly and efficiently collected. As for technical details, the paper starts with the deep learning-based OCNN algorithms, adopts a self-regulated resizing algorithm (SAR) and supports the concept of self-coding (SC) neural networks to assist with the multidimensional data of sports medicine research, to achieve successful secure prediction and assessment of sport injury-related diseases.

A. The following organization is the contribution of the work:

Section 3 The main objective of the work is to discuss the deep learning convolution network principle, algorithm and current problems of this paper. Which simultaneously analysis the, current problems with CNN algorithm-based sports medicine data analysis.

Section 4 The key algorithm for the improved CNN is evaluated based on Sect. 3 data, and the SAR algorithm with the SC function is introduced. Along with this, this segment will explain the neural network auxiliary model for convolution to achieve interpretation of sports injuries related to medicine results in a multi-dimensional manner.

Section 5 This segment deals with the research of in-loop cloud fusion equipment in the process to provide comparisons for the development of a true in-loop cloud fusion system to complete the building of an intellectual data framework for sports injuries related medicine.

Section 6 The entire text will be outlined in this segment and the relevant concerns addressed at a later date will be described.

3 Secure prediction and assessment of sports injuries using deep learning based convolutional neural network

In secure prediction diagnosis of sports injuries, the role of the neural network in large data management has been mathematically analysed based on the data collected through the convolution layer and the whole system's pooling process. Such two layers' extract and allocate the data collected to the whole link layer and the classifier for the related functionality. On the classifier, the whole link-layer operates based on the decision data, which is composed of probabilities and pooling data. In the stage of pooling, the main features are filtered and sub-sampling is analysed based on the CNN concepts. The standard CNN has constituted 1--3 layers of a feature extraction layer, and three layers of the artificial network which are primarily used with the accompanying whole link layer. The subsequent processing results are listed in the soft Max layer after the above-mentioned data processing.

(a) Study of structural hierarchy of CNN

The four computational layers regarding the mixture of huge information which correlates to the convolutional neural networks have been elaborated as follows:

1. Deep learning-based CNN layer

The deep learning convolution layer primarily contains the neural network filter that preserves a certain aspect ratio. For example, a filter of about $6 \times 6 \times 3$ size generally contains the first layer of traditional co-convolution neural network. When measuring the potential propagation layer, a filter needs to perform a traditional calculation on the input and the actual input value component needs to be determined in this calculation phase. The output data has been decreased after a range of convolution operations. At this point, the scale of the output and the quality of the actual data are almost having no difference with the reduction in the size of the preceding data.

In the real neural network training process, the purpose is to change the parameters in the middle of the convolution flow diagram iteratively to understand them. Weight sharing and local relations are the two most important characteristics of the convolution network. Simultaneously, a particular phase size parameter needs to be defined in the functional convolution measurement. If the phase size is 1.5, the related core slides one pixel based on the step size of 2.5 or even higher than 3.5, it will only shift 2 pixels in a time with its accompanying slide. The following details of the processing data convolution layer Using the big data sport-related injury based on convolution and approximation as shown in the Fig. 2.

Assuming that the amount of data on large sports medicine data for the input text in the Eq. (1). The i_n in the C function indicates the coefficient matrix (CNCI) as represented as follows,

$$CNCI = (c_{i1}, c_{i2}, c_{i3}, c_{i4}, \dots \dots ..c_{in}), \tag{1}$$

where, i_n in the C function indicates the coefficient matrix, In the corresponding section the CNCI for the above Eq. (1) has been represented in the following Fig. 2.

The convolution product of each data represents the data(n). The related nth data approximation is provided in Fig. 2 and represented as follows:

$$J_n^1 = xC_n + g^1. \tag{2}$$

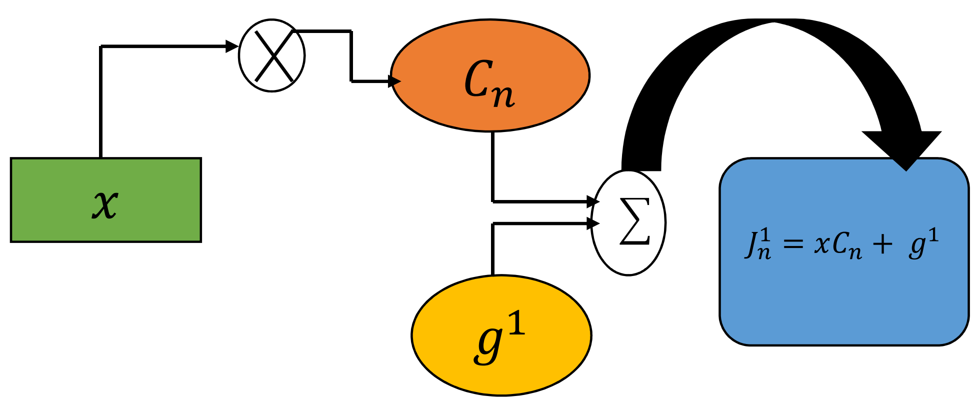

Fig. 2 Convolution and approximation

From the Eq. (2), if the convolution centre is n and window region is C_n. The vector J of the relevant J_n^1 represented in the Eq. (2) and The g^1 is an abnormality in the above Eq. (2) and the x is the related vector between the input sheet and the convolution row has been formulated for prediction diagnosis of sports injuries. Based on the mathematical computation, the optimized pooling layer has been defined as follows.

2. Optimized pooling layer

The pooling layer mainly encompasses the $J_n$performance of the layer in which Eq. (3) represents the maximum of n elements in J_n.

$$J_n^1 = tanJ\left(J_n^1\right). \tag{3}$$

The function of the pooling layer in the CNN is split into pools and the corresponding average pooling activity. In sports medical treatment, the optimum pooling procedure is typically used for extensive data analysis. The principal reason is the possibility that the results of sports treatment's large-scale details are not quite the same.

3. Optimized full link layer

In the optimized fully link layer, the neurons between two layers are entirely bound to the corresponding architectural layer behind the pooling layer, the resulting output of the pooling layer is as follows:

$$j_n^1 = XJ + G^4. \tag{4}$$

From Eq. (3), where the relevant j_n^1 is the output vector in the pooling layer, J is the whole link-layer output and G and X are the corresponded variance for prediction diagnosis of sports injuries. The related processing is shown in Eq. (4) for optimized output layer analysis.

4. Optimized output layer

As inferred from the Fig. 3. The output is based on the categorized softmax classification performance. When classifying, the classification method must be chosen based on the Eq. (5):

$$h(w) = \frac{g^w - g^{-w}}{g^w + g^{-w}} \tag{5}$$

$$h(w) = \frac{1}{1 + g^{-w}}. \tag{6}$$

As inferred From the Eqs. (5, 6), tan-h function $h(w)$ has two types of general functions of classification which correspond to the sigmoid. The g^w and g^{-w} corresponding to the equations are the measured optimized output parameters as shown in Fig. 3, further the SAR strategical method has been formulated as follows.

(b) Analysis of SAR algorithm

In the study of conventional algorithms, it is observed that the data sets are spread unevenly as data is interpreted by the subsequent algorithm for the accurate prediction diagnosis of sports injuries. In some groups, for example, the amount of experiments in the data sets is significantly larger. The transformation of size has been carried out in three modules. The appropriate training module, 1, 2 and 3. With the previous module, where every module has been linked. Module 1 of this type has a resolution of 64 × 164 × 3, module 2 has a resolution of 128 × 128 × 2 and module 3 of

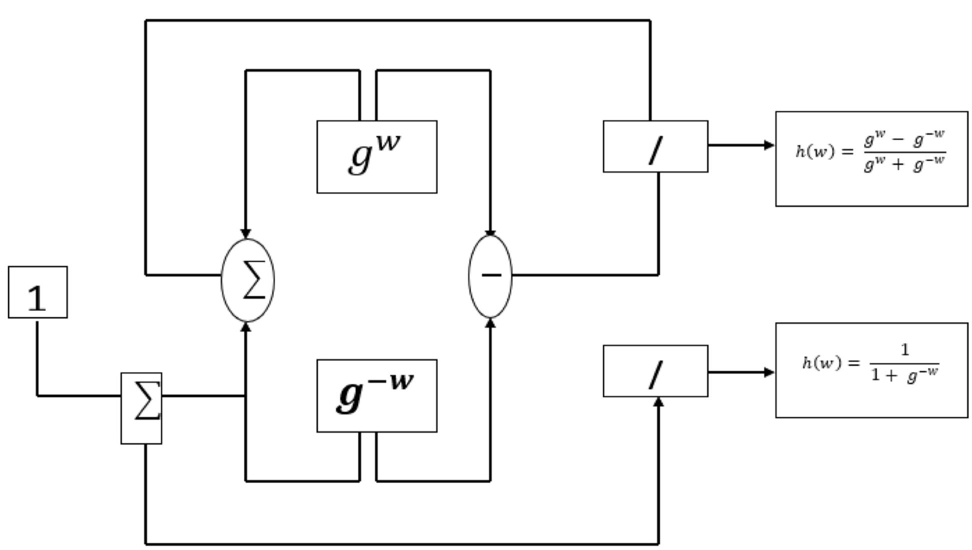

Fig. 3 Optimized output layer

that type has a resolution of 256 × 256 × 3. Unjustified distribution is termed imbalance. If no models are specifically qualified for the correct courses, those classifications will not have a strong ability to predict. This segment suggests a procedure to obtain sample equalization based on this principle and given the difference of the samples themselves. The key phenomenon of the SAR algorithm is shown in Eq. (7):

$$x_1 = x_{init} \cdot \alpha^s + x_{final}(1 - \alpha^s). \tag{7}$$

The x_1 is the present weight; the corresponding $x_{init} \cdot \alpha^s$ is the first value of the weight in the code; the matching $x_{final}(1 - \alpha^s)$ is the highest weight gained as output. α^s is the point over-index of the vector and s is the total number of times for the accurate prediction diagnosis of sports injuries.

In this segment the key theoretical points for resampling areas: includes A self-adjusting sampling (SC) which conducts a complex balance of groups of data, involves convergence I and fitting reduction J. Using the dynamic adaptive technique throughout the whole, the sampling has a feature of auto-adjustment and holds it based on the distribution for the originals as possible as which is shown in the Fig. 4. This paper uses spontaneous slicing methods to prevent recurrence and solve the problem of the minority class recurrence. It is clipped depending on the correct node level. Here, the Table 1 indicates the related size of clipping and the corresponding training cycle for the better self-regulation role of the neural network based on the above algorithm for the accurate prediction diagnosis of sports injuries. Has been obtained which are numerically represented as follows:

(c) Analysis of convolution SC algorithm

The secondary software self-coding convolution is primarily a supplementary mechanism in the primary one, where multidimensional data are mostly processed and analysed based on the performance of processing and evaluation. The SC neural network suggested in this paper primarily incorporates the configuration of

Table 1 Clip size for the accurate prediction diagnosis of sports injuries

Pre-edit dimensions	Post-edit dimensions
128 × 128	115 × 115
256 × 256	230 × 230
512 × 512	460 × 460

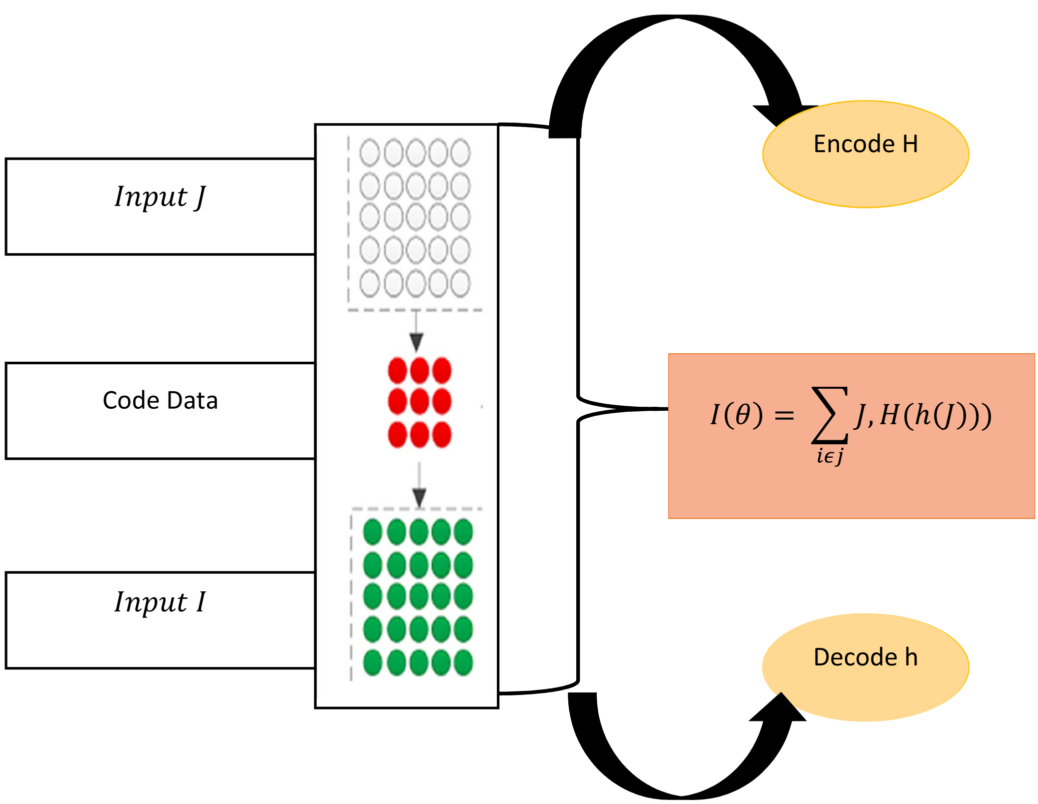

Fig. 4 Structure of self-coder

the neural network of self-coding convolution, determines the characteristic output layer map for the convolution and transforms the input data into a special dimension vector and executes a convolution process to achieve the corresponding effects for convolution. Coding, restoring and changing parameters are key design phases of the SC algorithm. Eventually, a corresponding optimization target function is obtained. The Eq. (8) indicates that the two-dimensional vectors are mainly converted into a single dimension:

$$I(\theta) = \sum_{i\epsilon j} J, H(h(J)), \tag{8}$$

where, $I(\theta)$ is the given input to the SC algorithm, H is the encoded output and h is the decoded output and J is the index value of the obtained encode and decode vectors. Sensor collection gathers data from the regions of abdominal and thoracic respectively. The frequency of CNN relates with inhalation and the cough identification. The splitting layer separates the input signal into the samples of abnormal values where the β_1 and normal values α_1 by sampling method:

$$\alpha_1(k) = a(2k + 1) \tag{9}$$

$$\beta_1(k) = a(2k), \tag{10}$$

where, $a(k)$ is input of splitting layer.

The term of α_1 indicates the forecast level values and term β_1 indicates the update level values respectively. Sampling rate stores the various tests of abnormal samples and normal samples for the accurate prediction diagnosis of sports injuries has been analysed based on the resulting degree of forecasting and updating determined from the following Eqs. (11, 12),

$$\alpha_2 = \alpha_1 - \theta © \beta_1 \tag{11}$$

$$\beta_2 = \beta_1 + \eta © \alpha_2, \tag{12}$$

where, θ indicates as weighting function. The term η indicates the update level and © indicates convolution operator respectively. In the proposed scheme CNN extracts from the sampling functionality and the constituents of splitting level, forecasts point and update level as available in the wavelet conversion for the accurate prediction diagnosis of sports injuries has been analysed. The appropriate input signals in the dividing level disintegrate into normal and anomalous samples based on the injuries:

$$\alpha_1^{(x)}(k) = a^{(x)}(2k + 1) \tag{13}$$

$$\beta_1^{(x)}(k) = a^{(x)}(2k), \tag{14}$$

where, $a^{(x)}(k)$ indicates the xth splitting level input, $\alpha_1^{(x)}$, $\beta_1^{(x)}$ indicates the x^{th} splitting level output. The splitting level evaluates forecast level with the output constituents as follows,

$$\alpha_2^{(x)} = s(\alpha_1^{(x)} - \theta^{(x)} © \beta_1^{(x)}) \tag{15}$$

where $\alpha_2^{(x)}$ indicates the output of x^{th} forecast level, $\theta^{(x)}$ indicates the weighting vector of x^{th} forecast level and the term © denotes the convolution operator respectively to analyse the .For the update level, CNN tests the output constituents as follows,

$$\beta_2^{(x)} = s(\beta_1^{(x)} - \eta^{(x)} © \alpha_2^{(x)}) \tag{16}$$

where $\beta_2^{(x)}$ indicates the x^{th} update level output, $\eta^{(x)}$ indicates the weighting vector of x^{th} update level and © denotes the convolution operator respectively. The simplification of CNN that is corrected based on the linear function as symbols has been shown in the Eqs. (17) and (18),

$$s(a) = \begin{cases} a, & if\ a \geq 0 \\ 0, & otherwise \end{cases}. \tag{17}$$

The task of t_1 and t_2 is derived from the update level performance as given in the Eq. (18)

$$t_b = \max \beta_2^{(3)}(n) \tag{18}$$

Classification is carried out in the analysis of sound signals to identify them. In feature extraction Gaussian mathematical (GM) structures used in various frameworks for the accurate prediction diagnosis of sports injuries. In a number of components, they can be used to quantify any probability density function. In fact, the injury processing tests has been shown to be strong enough. A different model is equipped for each class by comparing a corresponding function vector with parameter $\{x_a, \mu_a, G_a\}$, $a \in M$, where M is the amount of elements, x_a is theelement weight a, μ_a is the d-dimensional vector, with the average values for each characteristic, and G is the regression coefficients index. The Gaussian blend density $p(\mathrm{v}|\lambda_n)$ is modeled into a linear mixture of Gaussian multivariate PDFs, where v is a vector and λ_n is the GM of class n. The obtained $p(\mathrm{v}|\lambda_n)$ for each class to define a test function matrix. Here the Class n is classified to the evaluation function vector with the highest probability of $p(\mathrm{v}|\lambda_n)$. The $\{x_a, \mu_a, G_a\}$, M_n, n parameters for the λ_n GMM according to the class n which ideally fits the input data are obtained by a maximization expectation (EM) method. Every vector v function is constructed as a linear combination of Gaussian multivariates and the overall form as shown below:

$$p\left(\mathrm{v}\middle|\theta_a\right) = \frac{1}{(2\pi)^{\frac{d}{2}}\left|G_a\right|^2} i^{\left[-\frac{1}{2}(\mathrm{v}-\mu_a)^T G_a^{-1}(\mathrm{v}-\mu_a)\right]} \tag{19}$$

where $\theta_a = \left(\mu_a, G_a\right)$, v is a d-dimensional vector feature, μ is a d-dimensional vector, including every Function's mean value, G is the dxd regression coefficients index, $|G|$ is the deciding element. The full set of parameters for a M variable mixture is $\ominus = \left\{x_1, \ldots, x_M, \theta_1, \ldots, \theta_M\right\}$. Every GMM model λ_n for class n is functions as follows in the Eq. (20):

$$\lambda_n = \left\{x_m^n, \mu_m^n, G_m^n\right\}, \tag{20}$$

where $m = 1, \ldots, M$

The expectation-maximization (EM) algorithm used for calculating GM parameters in Eq. (21) is evaluated at this stage. The data point v in component m of given parameter $\ominus$ is defined as:

$$w_{am} = \frac{p_m\left(\mathrm{v}_a, \theta_m\right) \cdot x_m}{\sum_{k=1}^{M} p_k\left(\mathrm{v}_a\middle|\theta_k\right) \cdot x_k} \tag{21}$$

$$x_m^{new} = \frac{N_m}{N}, 1 \le m \le M \tag{22}$$

$$\mu_m^{new} = \frac{1}{N_m} \sum_{a=1}^{N} w_{am} \cdot \mathrm{v}_a, 1 \le m \le M. \tag{23}$$

For all parts m, $1 \le m \le M$ and all sample data a, $1 \le a \le N$. The E-step and M-step deploys an EM algorithm for every iteration. For all vectors v_a and all components m, then measure w_{am} as provided in Eq. (23) with Different parameters are determined for the accurate prediction diagnosis of sports injuries. Given $N_m = \sum_{a=1}^{N} w_{am}$ the amount of membership weights for the m^{th} element to get the mixture weights with loop simulation architecture which are expressed as follows.

(d) Algorithmic structure of the cloud fusion loop

Figure 5 shows the configuration of the cloud fusion device in this portion. The kernel of the relevant data center is OCNN suggested in this paper.

This segment provides the subsequent better architecture of the algorithm as shown in Fig. 5 based on the resampling algorithm and the convolutional learning model. This segment integrates a computer infrastructure, and the IoT analytics to create an in-loop simulation model for web-based applications and it will improve the sports injuries related medical data processing framework further, meet the requirements of sports-based health monitoring and solve the problems of the sophistication of sports medical datasets. The OCNN algorithm is used for the processing of data in the in-loop fusion simulation model.

1. General information storage

   The data collected in this process is passed through the control layer by the corresponding physical layer and sent to the stored data center for processing.
2. Implementation of user interface

   The architecture of the defined framework to collect the corresponding information does not include a physical layer interface nor does the data collection and analysis need to be done.
3. Privacy design

   To build the defined framework for access the corresponding data, no physical layer interface is required whereas, the data collection and analysis are essential.
4. Support design

   There are three layers in the architecture of the network model: the physical layer, the device layer, and the control layer. This includes sports health data in the physical layer which primarily links the physical layer to the application layer via control layer. It primarily provides device management services with various functionalities and resources while offering application layer services. The framework is built and implemented in the application layer, especially with the control of sports safety. The principal method of operation is: the correct detector interface which is identified and the appropriate medical details are collected. The data is accessed via the control layer from the cloud data center. For data acquisition, queries are first sent to the control layer and the required configuration data is subsequently sent to the control layer. The data is transmitted to the appropriate application layer by the control layer. The next three main formulas, based on the corresponding delay model, has the Jitter format and the performance in Eqs. (24, 25) and (26), should be implemented at the information transference stage.

$$\begin{cases} D = D_p + D_i + D_q \\ RDD = 2D \end{cases} \tag{24}$$

$$J = \frac{\sum_{i=2}^{\pi} RDD_i - RDD_{i-1}}{i - 1} \tag{25}$$

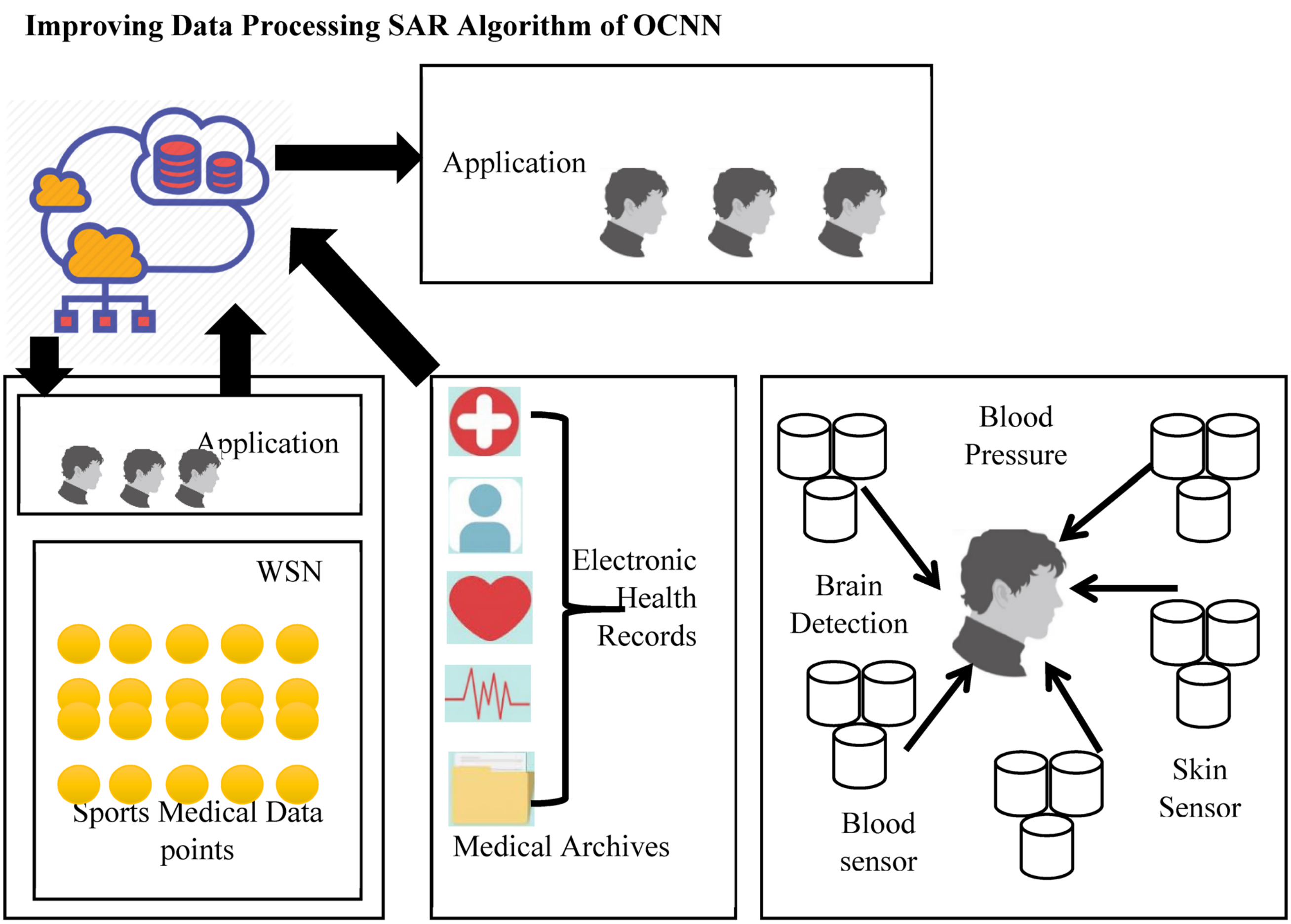

Fig. 5 In-loop simulation architecture

$$P = {}^{Q}\!/_{D}. \tag{26}$$

Equation (24) is the delay function, D, D_p, D_i, D_q is the delay time, Eq. (25) represents the jitter formula, i is the appropriate no. of nodes, Eq. (26) is the corresponding set where Q is the whole value of the corresponding value and P is the value of time of the corresponding value. The enhanced neural network suggested for this model is the database computing framework which Configure the nodes of data and the associated assignment fields is the appropriate data training flow from an advanced convolutional neural network. Reduce measurements of complex data and store them in the network layer. The testing nodes on a CNN Parameter Server. Pass data and related system models to various partitions via classification operations. The latest data parameters are spread in multiple assignment areas when the processing has been preheated to a certain level.

4 Results and discussion

This segment would perform theoretical analysis, where the medical data used are mostly from a professional sports laboratory, thorough testing of the in-loop simulation paradigm for sports medical data transmission. The parameters shown are the hardware parameters of this paper in Table 2.

This article analyses the relevant database with the optimized convolutional neural network (OCNN). This analytical data model dependent upon a young player of volleyball

Table 2 Technical in-loop parameters

Parameter	Value
Area	400×400
Mosel architecture	Random
Total nodes	160
Data transmission	3 Mbps
Transmission range	66 m
Total hops	4

accidents in a volleyball training camp. In its database, volleyball injuries are evaluated and assessed according to the injury severity of the participant contusion, joints spray. The document includes guidance for physicians and athletes to formulate recovery treatment plans based on such data, using the review and evaluation of the grades of injury and the intervention avoidance guide. The related database-based research is as below:

The related latency scheme in the Sports safety IoT system is shown in Fig. 6, dependent on the above-noted experimental conditions. The file size is 652 kB, the corresponding packet is 802B-1202B and it is having 65B increment and the transmission rate is 0.09 s. Since the $\beta_2^{(x)}$ indicates the x^{th} update level output, $\eta^{(x)}$ indicates the weighting vector of x^{th} update level and © denotes the convolution operator respectively to reduce the latency level. The simplification of CNN that is corrected based on the linear function as symbols has been shown in the Eqs. (17) and (18),

The impact of the rate of transmission and the packet size with an average delay is shown in Fig. 7. From the calculation, if the transmitting rate is 0.05--0.08 s. the increase is 0.03 s respectively.

Figure 8 shows the effect on the average latency of different packet sizes and transmitting speeds. The graph shows that if the rate of transmission correlates to approximately 0.03 s, the larger the associated packet, the greater the subsequent delay, and the smallest acceptable max delay is calculated. The impact of various sizes of data and propagation periods on delay in the internal environment is measured in terms of internal delay. The above figure shows that the packets transfer speeds have a little negligible result on internal delay.

The split line diagram shows that the data packet would fail when the transmission rate between 0.02 and 0.04 s. The size of the data packet is 1302B so when the transmission speed is 0.03, the resulting transmitting impact is maximum and the latency for transmission is zero.

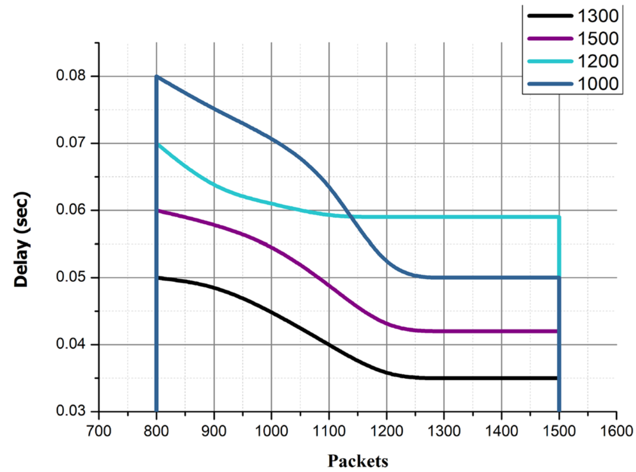

Fig. 7 Impact on the transmission rate and packet size

To further validate the benefits offered in this paper by the enhanced neural network convolutional algorithm. Based on the cloud-based simulation environment provided by the hardware on the system, various common models are compared to the enhanced profound analysis algorithms model.

The key parameters are the accuracy of tests and the coefficient of correlation. Similar to the deep learning algorithm, three main models are available in traditional networks: the CNN model, the ANN model, and the machine learning (ML) algorithm. This project carried out 20 confidential tests, with data cross-validated for each experiment, guaranteeing the same data packets size with optimized density curve as shown below in the Fig. 9, and ensuring the same size and rate of transmission never changed.

The related split line diagrams for test accuracy are shown in Fig. 10. The accuracy over classifications of the enhanced CNN model is approximately 80% as compared with other metrics with 59%, and 55% accuracy have been obtained

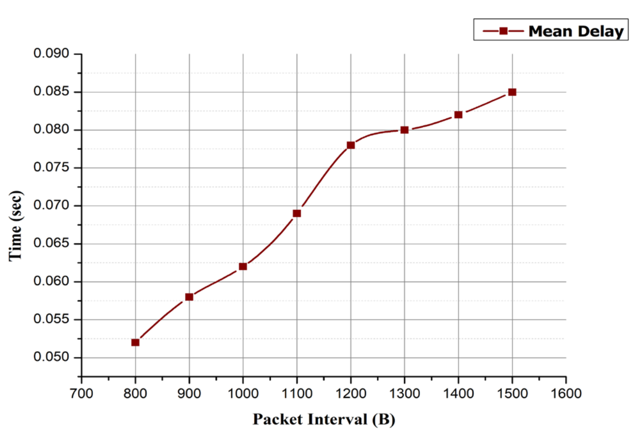

Fig. 6 Related latency

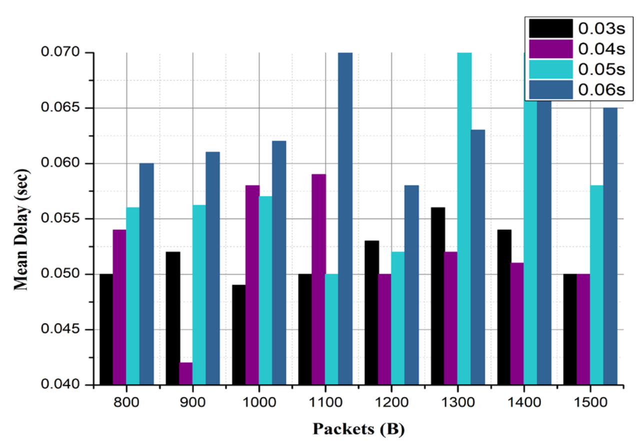

Fig. 8 Average latency of different packet size

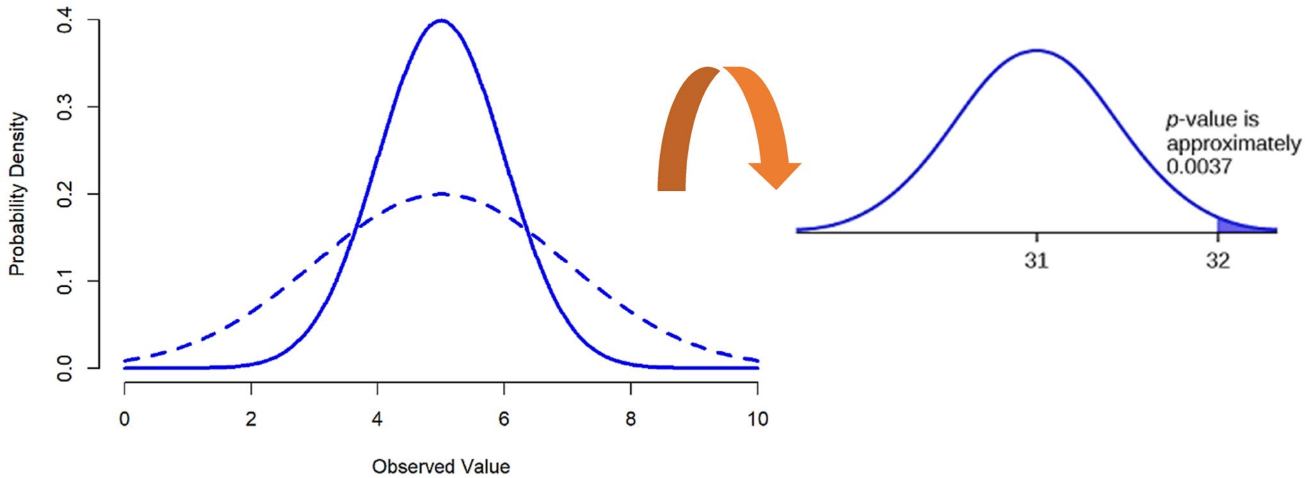

Fig. 9 Optimized density curve analysis

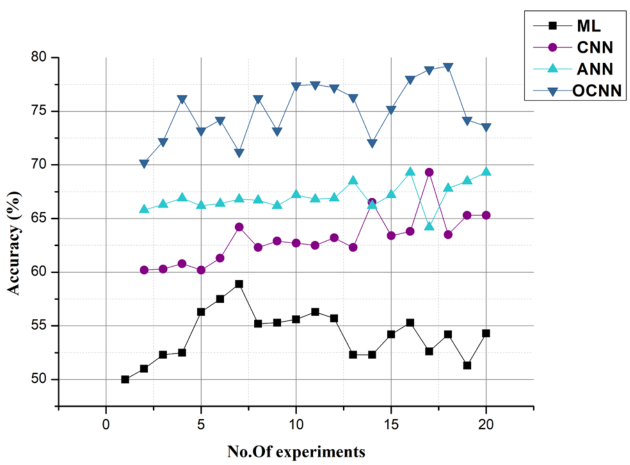

Fig. 10 Accuracy rate of various algorithm

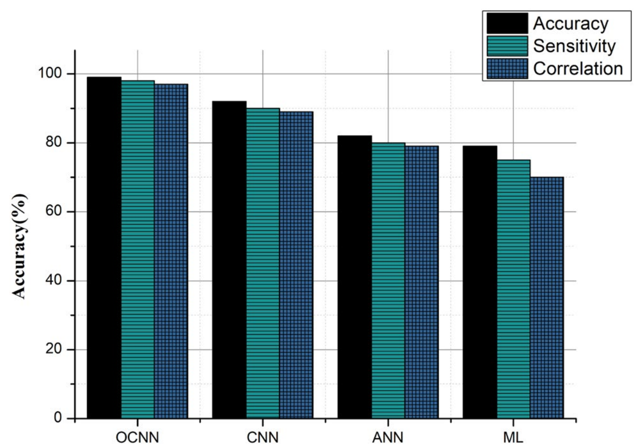

Fig. 11 Precision on the transmission rate and packet size

in classification by corresponding neural network standard, Here the model for AI networks and machine learning algorithm respectively has been used Along with the accuracy of training, This article verifies the diagnostic accuracy over the precision of optimized neural network models, traditional neural network models, AI network models and an ML algorithm based on an in-loop fusion system.

As shown in Fig. 11, with the hypothesis of the same number of basic layers, 95% of the predictive precision of enhanced innovative neural networks and conventional neural network approaches above can be achieved. The OCNN structure proposed in this paper provides clear merits compared with others. The E-step and M-step deploys an EM algorithm for every iteration. For all vectors v_a and all components m, then measure w_{am} as provided in Eq. (23) with different parameters are determined for the accurate prediction diagnosis of sports injuries.

5 Conclusion and future outcomes

The market for data processing and computational services is growing with the rise in sports medical data. With the huge increase in details, conventional algorithms for deep learning in sport medical data mining appear weak and inefficient. Consequently, sport medical methods are important and meaningful in their quality and precision. In the framework of this research, the drawbacks of the current convergence of the neural network algorithm together with sports medical data are extensively evaluated and tested and the algorithms of neural networks that converge with the SAR-function algorithm which are strengthened. This paper incorporates the supplementary convolution algorithm SC-NN model to process vast amounts of data more efficiently, in addition to modelling and analysis of multi-dimensional sports medicine results. Eventually, to create a smart data infrastructure for sports injuries related to medicine, this paper establishes and constructs an in-loop fusion application and conducts comprehensive study and software testing, thus giving the actual in-loop fusion hardware in-loop device technical support and expertise. Overall, this article is fairly comprehensive, because of its limited space, the research on following-up must concentrate to achieve an effective evaluation of the sport-injury image data with enhanced neural touch in the time series data function testing.

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