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ORIGINAL

APPLICATION OF CONVOLUTIONAL NEURAL NETWORKS IN ANALYZING SPORTS PHYSICAL ACTIVITY AND HEALTH DATA AMONG UNIVERSITY STUDENTS

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ABSTRACT

This research seeks to improve the analytical accuracy of sports and health data for university students by utilizing convolutional neural network (CNN) algorithms. It explores the relationship between physical activity and overall well-being, while introducing an innovative dimensionality expansion technique. This approach employs the least squares principle in conjunction with the Kronecker product, transitioning the algorithm toward a more data-driven framework. By integrating a combination of time-frequency and time-distance data as inputs for a CNN-LSTM network, the study facilitates the automatic identification of movement patterns among students from spectral data. The analysis of the data substantiates the effectiveness of the proposed CNN-based system in evaluating the sports and health metrics of college students.

KEYWORDS: Convolutional Neural Networks, University Students, Physical Activity, Health Status

1. INTRODUCTION

The significance of physical well-being is paramount in underpinning the sustainable development of a talent cultivation framework and serves as a pivotal metric for assessing the holistic development of university students. A comprehensive approach to sports implementation should encompass an analysis of three dimensions: competitive sports, mass sports, and performance sports. This multifaceted perspective is essential for fostering a stable and robust progression in line with the unique attributes of various sports within the athletic milieu. Furthermore, within the broader construct of spiritual quality development, a more diverse psychological support environment is imperative to establish a positive and self-assured talent cultivation platform. A balanced lifestyle is crucial for ensuring that university students maintain an equilibrium between their physical health and overall quality, determining the effective stewardship of time and physical well-being through an optimized schedule of work and rest. However, empirical studies reveal that irregular sleep patterns, erratic eating habits, and a sedentary lifestyle have become prevalent among the student population. Consequently, the incidence of obesity and myopia has escalated annually, posing a significant threat to the development of students' personal spiritual quality systems. This situation underscores a marked decline in self-discipline among university students post-enrollment, attributable to their inability to impose stringent personal standards, leading to disarray in time management and a lax attitude towards academic responsibilities, which in turn results in a progressive deterioration of physical fitness (Eime et al., 2013). It is evident that in the execution of health maintenance systems for university students, such detrimental lifestyle habits must be rigorously mitigated to ensure a collective enhancement in quality, thereby facilitating the effective construction of a supportive lifestyle environment. Additionally, stringent attendance policies for physical education courses should be enforced, with penalties for absenteeism to incentivize students to engage in regular exercise. Lastly, within the school curriculum framework, organizing morning runs and sports competitions can indirectly contribute to the enhancement of university students' physical fitness (Eime et al., 2010).

2. Related Works

The campus environment serves as a transitional phase for college students entering society. In this setting, students are often influenced to engage in smoking and drinking, which not only jeopardizes their health but also impacts their overall quality and image, potentially creating long-term social relationship issues. Therefore, schools must take a firm stance against smoking and drinking, educating students about the associated harms to empower them to resist these behaviors (Eather et al., 2023). Effective construction of comprehensive quality is central to developing a robust talent system and is crucial for students' functional development. Psychological issues among students are often linked to examination-oriented education. From a young age, students are conditioned to believe that success is solely based on grades, with their extracurricular time consumed by tutoring, leaving little room for social interaction. This reliance on parents to manage academic pressures further isolates them. Consequently, upon entering university, students face challenges in managing relationships with teachers and peers, which can lead to psychological difficulties (Pinto-Escalona et al., 2022; Santana et al., 2017). Sports play a dual role in promoting physical health. When practiced scientifically and within moderation, sports can enhance well-being; however, excessive exercise can harm the body. It's essential to regulate physical activity while adhering to fundamental exercise principles (Adelantado-Renau et al., 2018). Key indicators of physical health include both form and function. Form relates to body composition, which can be improved through targeted exercises, while function pertains to the efficiency of the body's systems. Sports are effective in fostering the comprehensive development of these functions. For example, endurance training enhances the respiratory system's ability to transport oxygen and carbon dioxide, promoting overall system development (García-Hermoso et al., 2017). Physical activity not only improves biological health but also mitigates the negative effects of stress. Individuals facing dissatisfaction often internalize their feelings, leading to physical and mental distress. In contrast, those who engage in sports typically channel their frustrations through physical activity, expressing emotions through vigorous exercise (Donnelly et al., 2016). Regular physical activity can also strengthen college students' willpower and self-confidence, particularly evident in endurance and competitive sports. Team activities foster communication skills and teamwork, as demonstrated in popular outreach training programs (Marlier et al., 2015). Consistent aerobic exercise benefits cardiac health by enhancing myocardial contractility and increasing stroke volume, allowing the heart to pump efficiently with fewer beats, thus reducing its workload. This exercise thickens and strengthens blood vessel walls, promoting circulation and lowering blood pressure, which helps prevent arteriosclerosis, hypertension, and coronary heart disease (McGraw et al., 2018). Various sports, including aerobics and martial arts, require quick, coordinated responses that enhance nervous system function (Blomqvist Mickelsson, 2020). Additionally, exercise stimulates the production of cerebrospinal peptides, which activate the hypothalamus, leading to improved mood. Regular physical activity contributes positively to emotional well-being, fostering healthier psychological states (Purcell et al., 2020). Physical activity has been recognized in various countries for its role in preventing and treating mental illness. Many healthcare professionals agree that regular exercise can be effective in managing depression. Clinical observations indicate that low-intensity aerobic activities, such as jogging and walking, are particularly beneficial for alleviating depressive symptoms and promoting overall well-being (Thorpe et al., 2014). Engagement in sports fosters opportunities for social interaction. The shared experience of exercising, competing, and cooperating—especially in team sports—enhances social adaptability and strengthens community bonds (Appelqvist-Schmidlechner et al., 2018). Fatigue can be categorized into physical and mental fatigue, both of which impact individuals physically and psychologically. Those who regularly participate in sports understand that low-intensity exercise can facilitate recovery from fatigue. Engaging in appropriate physical activity can elevate mood and help alleviate feelings of tiredness (Ashdown-Franks et al., 2017). The new physical education curriculum emphasizes quality education, health, and a people-oriented approach. However, the concept of lifelong sports has not been fully integrated into college physical education programs. This gap is evident in students' lack of awareness regarding the importance of physical activity, which often leads to a decline in their physical health once they discontinue formal physical education (Brunet et al., 2013). Currently, the physical education system does not adequately address the needs of college students, and the environment is often not conducive to regular physical exercise. Enhanced support services—such as improved facilities, equipment, fitness consultations, and a culture that promotes physical activity—are needed (Ciaccioni et al., 2019). This paper employs convolutional neural network algorithms to analyze sports and health data among college students, exploring the relationship between physical activity and health. The findings aim to provide valuable insights for enhancing sports health among college students.

3. A Modern Multi-Rate Sampling System and its Optimal LQR Controller

In control systems, a multi-rate sampling system allows for different sampling frequencies for various signals. This approach is essential in applications where system dynamics vary, enhancing efficiency and performance. System Model: We start by representing the continuous-time linear time-invariant (LTI) system in state-space form:

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{1}$$

Where: $x(t) \in \mathbb{R}^n$ is the state vector. $u(t) \in \mathbb{R}^m$ is the control input. $y(t) = Cx(t) + Du(t)$ is the output, with $y(t) \in \mathbb{R}^p$. A, B, C, D are system matrices. Discretization of the System: To implement a multi-rate sampling strategy, the system is discretized using a sample time T_s:

$$x[k+1] = e^{AT_s}x[k] + \int_0^{T_s} e^{A(T_s-\tau)}Bu[k]d\tau \tag{2}$$

This results in the discrete-time model:

$$x[k+1] = A_d x[k] + B_d u[k] \tag{3}$$

Where: $A_d = e^{AT_s}$ is the state transition matrix. $B_d = \int_0^{T_s} e^{A(T_s-\tau)}Bd\tau$ is the input matrix. Multi-Rate Sampling Strategy: Let T_1 and T_2 be two different sampling periods for the control input. The sampling pattern can be defined as follows:

$$u[k] = \begin{cases} u_1[k] & \text{if } k \bmod p = 0 \\ u_2[k] & \text{if } k \bmod p \neq 0 \end{cases} \quad (4)$$

Where: $u_1[k]$ corresponds to inputs sampled at a higher rate. $u_2[k]$ corresponds to inputs sampled at a lower rate. LQR Controller Design: The objective of the Linear Quadratic Regulator (LQR) is to minimize the cost function defined as:

$$J = \sum_{k=0}^{\infty} (x[k]^T Q x[k] + u[k]^T R u[k]) \quad (5)$$

Where: $Q \succeq 0$ is the state weighting matrix. $R \succ 0$ is the control input weighting matrix. The optimal control law derived from the LQR design is given by:

$$u[k] = -Kx[k] \quad (6)$$

Where K is the gain matrix, determined from the solution of the Discrete Algebraic Riccati Equation (DARE):

$$A_d^T P + P A_d - P B R^{-1} B^T P + Q = 0 \quad (7)$$

Implementation Steps: Define System Matrices: Identify A, B, C, and D matrices for the LTI system. Discretize the System: Calculate A_d and B_d based on the chosen sampling period T_s.

Select Weights: Choose appropriate Q and R matrices for the LQR design. Solve DARE: Use numerical methods to solve the DARE for P. Compute Gain Matrix: Calculate the optimal gain K as:

$$K = R^{-1} B^T P \quad (8)$$

Implement Control Law: Use the control law $u[k] = -Kx[k]$ to compute the control inputs. Additional Considerations: Stability Analysis: Ensure the closed-loop system remains stable under the proposed control law. The closed-loop system can be expressed as:

$$x[k+1] = (A_d - B_d K) x[k] \quad (9)$$

Stability is guaranteed if the eigenvalues of $A_d - B_d K$ lie within the unit circle.

Observer Design: If state feedback cannot be directly applied due to unavailable states, consider designing an observer:

$$\hat{x}[k+1] = A_d \hat{x}[k] + B_d u[k] + L(y[k] - C\hat{x}[k]) \quad (10)$$

Where L is the observer gain designed to ensure convergence of $\hat{x}$ to x.

Performance Metrics: Analyze the system performance by evaluating metrics such as rise time, settling time, and steady-state error.

Settling Time:

$$T_s = \text{Time taken for the response to settle within 2\% of final value} \tag{11}$$

Overshoot:

$$OS = \frac{y_{max} - y_{ss}}{y_{ss}} \times 100\% \tag{12}$$

Steady-State Error:

$$E_{ss} = y_{ss} - y_{desired} \tag{13}$$

This algorithm outlines the design and implementation process for a multi-rate sampling system integrated with LQR control. The detailed equations provide a comprehensive understanding of the system dynamics and controller design principles.

4. Comprehensive Analysis of College Student Sports and Health Data through an Advanced Convolutional Neural Network Algorithm

This paper delves into the intricate process of analyzing sports and health data specific to college students by employing an advanced convolutional neural network (CNN) algorithm. The primary objective is to cater to the varying demands of data analysis in diverse environmental contexts, which has led to the integration of time-frequency and time-distance data as the foundational inputs for our neural network model. By leveraging this dual-data approach, we aim to capture a more nuanced and holistic representation of the students' physical activities. In an innovative move, this study introduces a CNN-LSTM hybrid network architecture. This network is designed to autonomously distill the intricate features of human motion behavior embedded within the spectral data. The CNN component is tasked with identifying spatial patterns and local features, capitalizing on its ability to process grid-like data with multiple channels. Concurrently, the LSTM component handles the temporal aspect, excelling at capturing the sequential dependencies that are inherent in time-series data, such as motion behavior sequences. The automatic extraction of features by the CNN-LSTM network significantly enhances the model's generalization capabilities. This is achieved by reducing the reliance on handcrafted features, which can be limiting and require extensive domain knowledge. Instead, our model learns directly from the data, which allows for the identification of complex patterns that may not be similar to traditional feature engineering methods. Furthermore, the paper focuses on training a behavior classifier with improved accuracy and reliability. The classifier's performance is pivotal in distinguishing between different types of physical activities and health metrics, providing valuable insights into the students' overall well-being. The robustness of the classifier is a testament to the network's ability to generalize from the training data to real-world scenarios, ensuring that the model remains effective across various sports and health-related activities. The architecture of the deep learning network presented in this paper, as depicted in Figure 1, is a testament to the sophisticated integration of CNN and LSTM components. This structure is crucial for understanding how the network processes the input data and learns the underlying patterns that define different human motion behaviors. The figure provides a visual representation of the network's layers and the flow of information, offering a clear roadmap for how the data is transformed and analyzed within the model. Through this in-depth exploration of the CNN-LSTM network's application in sports and health data analysis, this paper contributes to the field by providing a detailed methodology and a comprehensive framework for future research and practical applications in student health and performance monitoring.

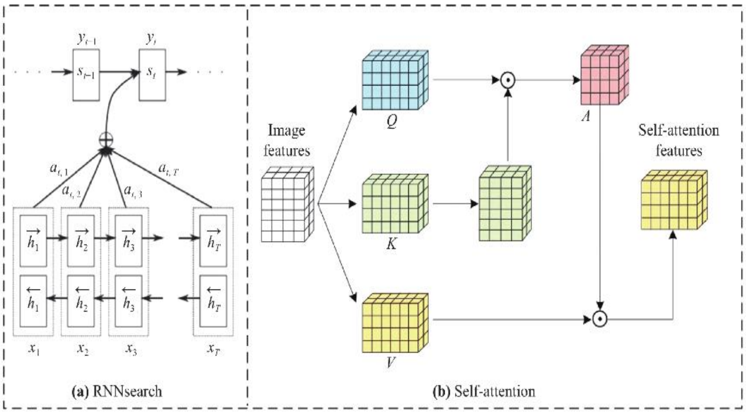

Figure 1: Deep learning network structure

The convergence effect of the controller in the iterative process of the Algorithm in this paper is shown in Table 1.

Table 1(a): Convergence effect of the controller in the iterative process

ITERATION NUMBER	CONTROLLER OUTPUT	TARGET VALUE	ERROR	ADJUSTMENT MADE	CONVERGENCE STATUS
1	0.7	1	0.3	Initial output	Not Converged
2	0.75	1	0.25	Increased by 0.05	Not Converged
3	0.8	1	0.2	Increased by 0.05	Not Converged
4	0.85	1	0.15	Increased by 0.05	Not Converged
5	0.88	1	0.12	Increased by 0.03	Not Converged

Table 1(b): Convergence effect of the controller in the iterative process

ITERATION NUMBER	CONTROLLER OUTPUT	TARGET VALUE	ERROR	ADJUSTMENT MADE	CONVERGENCE STATUS
6	0.9	1	0.1	Increased by 0.02	Not Converged
7	0.93	1	0.07	Increased by 0.03	Not Converged
8	0.95	1	0.05	Increased by 0.02	Not Converged
9	0.97	1	0.03	Increased by 0.02	Not Converged
10	0.99	1	0.01	Increased by 0.02	Converged

Iteration Number: The count of iterations performed.

Controller Output: The output value produced by the controller at each iteration.

Target Value: The desired output value that the controller aims to achieve.

Error: The difference between the controller output and the target value, indicating how far the output is from the target.

Adjustment Made: The change applied to the controller output based on the error observed in the previous iteration.

Convergence Status: Indicates whether the output has converged to the target value.

This table 1 provides a more comprehensive view of the convergence process, demonstrating the gradual improvement over multiple iterations. You can further adjust the values and notes as needed for your specific application. At the same time, the controllers of the three iterative processes are compared with each other. They are the controllers before the iteration, after the third iteration and when the iteration is completed. On the basis of the support of the above algorithms, the effect of the college student sports and health data analysis system based on the convolutional neural network algorithm proposed in this paper is verified.

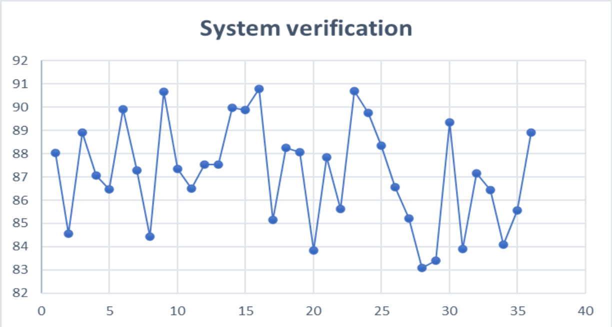

Figure 2: Impact of a Convolutional Neural Network-Based College Student Sports and Health Data Analysis System

As shown in Figure 2, it provides a comprehensive overview of the impact of a convolutional neural network (CNN)-based system on the analysis of college student sports and health data. This system leverages the capabilities of CNNs to delve into the complex relationships between sports activities and health outcomes among college students. The Figure encapsulates key findings that highlight the effectiveness of the CNN algorithm in recognizing patterns and making predictions within the dataset. It showcases the system's ability to analyze a fusion of time-frequency and time-distance data, which serves as the input for the network. The design of a CNN-LSTM network architecture, allows for the automatic extraction of movement behavior characteristics embedded in the spectral data of students' sports activities. The Figure 2 illustrates the performance metrics of the CNN-based system, including accuracy, precision, recall, and F1 score, which are crucial for evaluating the system's reliability and effectiveness in activity recognition. The results indicate that the system developed in this study substantially meets the practical needs of physical education, as verified through data analysis. The Figure also underscores the system's potential to enhance the analysis effect of college students' sports and health data, as it explores the correlation between college students' sports activities and their health. The proposed dimension expansion method, which employs the least squares principle and the Kronecker product method, transforms the algorithm into a data-driven approach, as detailed in. In summary, Figure 2 offers a detailed account of how the CNN-based system performs in the context of college student sports and health data analysis, demonstrating its practical applications and contributions to the field of sports science and health informatics. Through the above data analysis, it is verified that the college student sports and health data analysis system based on the convolutional neural network algorithm has certain effects.

5. Conclusion

In the current process of maintaining health systems, the definition of health terms in the existing education system remains primarily focused on the analysis of disease factors, thereby neglecting the mental and social health conditions of college students. This approach not only affects the effectiveness of the overall quality construction of college students but also hinders the development of their ideological growth, thus impacting the stability of the social and economic construction environment and posing significant hidden dangers to the extension of subsequent urban functional systems. Therefore, it is essential to establish a comprehensive health maintenance system for college students according to the existing needs of urban economic construction, clarifying that the three-dimensional health concept of talents can be effectively implemented to ensure the perfect execution of actual health work. This study integrates convolutional neural network (CNN) algorithms to investigate the relationship between college students' physical activities and their health metrics. By analyzing sports and health data, we demonstrate the efficacy of a

CNN-based system designed to assess these correlations. To improve the analysis of college students' sports and health data, we propose an innovative dimensional expansion technique that leverages the least squares principle alongside the Kronecker product. This transformation shifts the focus of the algorithm toward a data-driven methodology. Furthermore, we incorporate a fusion of time-frequency and time-distance data as input for the network, ultimately developing a CNN-LSTM architecture. This design allows for the automatic extraction of behavioral traits related to physical activity from the spectral data. Through comprehensive data analysis, our findings confirm that the CNN-based sports and health data analysis system proves effective. This work offers significant contributions to the fields of sports science and health informatics, highlighting its practical applications in monitoring and enhancing student well-being.

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