Application of Internet of Things Framework in Physical Education System

Lixun Hu[1,2], Caili Liu[2], Korhan Cengiz[3,5], Gunasekaran Nallappan[4]

[1] Shaanxi University of Chinese Medicine, China
[2] Xi'an International University, China
[3] Department of Electrical-Electronics Engineering, Trakya University, Turkey
[4] Department of Advanced Science and Technology, Toyoto Technological Institute, Japan
[5] College of Information Technology, University of Fujairah, UAE

lclhuchmao@sina.com, xty05hulixun@sina.com, korhancengiz@trakya.edu.tr, gunasmaths@toyota-ti.ac.jp

Abstract

Recently, students engage in physical activities to promote physical, mental, and psychological benefits globally. Many schools employ the physical education system as an integral part of their curriculum to develop their students. This paper presents the main benefits of the physical education system. Further, the pillars of physical education in the modern education system are also analyzed. The usage of the Internet of Things (IoT) framework in the physical education system is also being presented in this research. We also propose a new framework called the IoT-based Physical Activity Recognition (IPAR) model. In this model, physical action recognition is done using data from a single tri-axial accelerometer. The recognized action and medical parameters like accelerometer, oxygen level, pulse rate, and temperature are transferred through the cloud to the physical activity instructor's mobile phone. The proposed physical action recognition model produces an overall accuracy of 95.82%. Further, the overall F-score attained by the proposed IPAR algorithm is 97.83%. Moreover, the overall time complexity of the proposed IPAR algorithm was as low as 53.96ms.

Keywords: Physical education, F-score, Recognition, Accelerometer, IoT, Cloud

1 Introduction

Physical education is an essential part of the educational curriculum. Children who engage in physical activities have enhanced physical fitness, increased mental focus, decreased cardiovascular issues, and improved learning capabilities. Recently, physical education is represented in website information to increase students' involvement in physical activities. Public websites are designed to support physical activity programs [1]. There are also special schools that aim at providing dedicated physical education. These schools have the culture of giving training in various aspects of physical education using support assistants [2]. For students with visual impairments, physical education helps in increasing articulation capabilities. The device can be evaluated by telephone—accurately designed physical fitness programs to achieve the chosen objectives. Significant risk factors for heart disease can be accounted for in physical education: obesity, inactivity and high blood pressure. An effective program improves muscle strength, endurance, resistance to muscle, fat-to-muscle body composition and cardiovascular stamina for kids. The active program helps the children regulate their weight by burning calories, tones, and enhanced body structure. Quality physical training can affect moral growth. Students are given the chance to take responsibility for their own decisions, to collaborate with others.

They can be easily implemented in residential schools [3]. The relationship between schools, teachers, and the physical education system is crucial. This analysis can be done using semi-structured interviews. These interviews are conducted between the physical education coaches and the teachers [4]. The evaluation of teaching sustainability can be done using psychological flexibility analysis. Psychological versatility implies "to contact the current moment fully as a conscious being and, in the service of the values chosen, to change or to perpetuate the situation." In daily words, this means keeping our thoughts and emotions light rather than short term urges, thoughts and feelings and acting on long-term principles and objectives. Psychological versatility spreads across a broad spectrum of human capacities throughout order: to understand and adjust to different needs; to modify mentalities or behavioural repertoires when specific techniques compromise personal or social operations; to maintain harmony between essential fields of life

*Corresponding Author: Lixun Hu; E-mail: lclhuchmao@sina.com
DOI: 10.53106/160792642021112206017

and to be aware, responsive and dedicated to comport ages that adhere to strongly held values.

The sense of purpose is another important property of physical education sustainability [5]. Showering culture is connected to the physical education system. Physical activity at any age is essential not only for weight loss besides for disease prevention, better mood and overall health. Although you may have emphasized the importance of exercise for your children when they grow up, children have a lot less power over what they are doing once they are out of the house. Community-based physical activity support actions integrate physical activity incentive with social support to create, improve, and sustain social networks that promote meaningful behaviour change. Education, community or individual counselling, or personalized plans may have been used as intervention measures. Examples are walking groups, creating an exercise buddy system, drawing up contracts, targets, or physical activity planning.

This has a direct effect on sport and leisure activities. Physical and cultural practices are responsible for the mental development of school-going children [6-9]. An essential attribute of physical activity is a fundamental motor skill. Motor competence improves the level of physical action that children can perform [10]. Motor proficiency aids in the increase in physical and mental fitness [11-13]. Daily exercise may have a profoundly beneficial effect on depression and anxiety. Instead, it relieves stress, improves memory, reduces stress and improves the overall mood. And to enjoy the benefits you do not have to be a fitness fan. Research shows that small quantities of workout can make a real difference. Regardless of your age and fitness level, you will learn to use exercise as a powerful tool to cope with mental illness, boost energy and insight and improve life. People who regularly practice appear to because they feel incredibly well.

Striking and fielding games are the popular physical education games employed in the school physical education system. Teachers have the responsibility to promote the incorporation of physical education in the educational curriculum [14]. Physical fitness practices in schools must be based on psychological attributes. These attributes are essential during the transition from childhood to adolescence [15-16]. There are several culturally diverse schools. In these schools, it is the teachers' responsibility to determine the appropriate physical activity for each type of student [17].

2 Related Work

To et al. [18] has proposed a scheme for physical education programs using the Vietnamese Education System. In this paper, eight different schools were used for analysis. Interviews were conducted for the class teachers and the physical education instructors. It was inferred that the best results were observed when the children spent 33% of their time on physical education. Telford et al. [19] analyzed the outcome of the incorporation of the physical education system in the existing educational system. This work was aimed at improving physical literacy in the school education system. Students belonging to the fifth grade were employed for analysis. This analysis was conducted for 33 weeks.

Quintas et al. [20] presented a framework for understanding the physical education system's psychological effects. In this paper, the natural experiments were conducted using four schools. Gamified interventions were included in the school education system. It was inferred that no interaction effects were using gamified interventions. Telford et al. [21] presented a scheme for identifying school outcomes using a physical education system. This study aimed to improve physical literacy. A cluster-randomized approach scheme was employed in this paper. This scheme was aimed at the sub-urban primary schools.

Borgen et al. [22] identified the difference between physical education and health initiatives. The relationship and difference between the theoretical effects and practical effects of school education were analyzed. It aided in understanding the boundary maintenance problem for the physical education system. Bopp et al. [23] examined the various ethical concepts behind social media usage in physical education. In this paper, social media was integrated with the physical education system. Besides, this paper analyzed how wearable sensors can promote physical education amount the youth. Social media use in education refers to social media online in academic from primary, secondary and post-secondary education. Social media are becoming more available and easier to use, meaning that younger and younger are students, capable of knowing and using social media. Social media can be interpreted as a kind of repository of ideas and other media accessible day or night by their users. As input could be generated more easily over social media, a contact gap between students and teachers has been bridged and unprecedented. As pupils were almost instantly able to view and respond, it turned out to be a deeper understanding of class material through this improved contact.

Wang et al. [24] investigated various student-related factors that influence the physical education system. Six different elementary schools were used for the investigation. It was found that the combination of female students with disabled students in physical education produced positive results that aided in improving physical education in the educational curriculum. Burnett [25] presented a scheme for evaluating the status of physical education in schools. In particular, South African schools were considered for this study. Totally 9 provinces of South Africa were considered for evaluation. In these provinces, a total of

61 schools were selected. It was found that physical education was taught using 25.1% of the total number of teachers available in the school.

Mangione et al. [26] designed a scheme for mapping the model of physical education. This system was designed for Irish schools. 67 primary schools were used for analysis. Here, physical education was rendered with the help of non-specialist teachers. In this paper, the privatization of physical education was also considered. Fletcher et al. [27] have proposed a system in which a multi-dimensional concept was used for physical education. Here multiple schemes were evaluated to understand the effects of each dimensional view on the physical education programs. Besides, competency-based approaches were also assessed and were found to produce outstanding results.

Based on these investigations, we have developed a scheme for physical education using the Internet of Things scheme to improve school children's mental and physical fitness.

The contributions of this paper are as follows:

- The benefits of the physical education system are presented.
- The pillars of physical education in the modern education system are analyzed.
- Usage of the Internet of Things (IoT) framework in the physical education system is presented.
- A new framework called the IoT-based Physical Activity Recognition (IPAR) model is proposed.
- The benefits of the proposed IPAR model are presented.
- The proposed IPAR model is compared with other traditional machine learning algorithms for physical activity recognition.

3 Proposed Methodology

3.1 Physical Education System Benefits

Physical education is an essential component of the modern education system. It not only enhances the physical attributes of the children but also increases their mental qualities. Physical movements should be incorporated into young children's lives to form a basis for their campaign and action throughout their lives. Children with higher physical activity levels are likely to be more involved in their childhood even after maturity. Early physical activities have various advantages, which go far beyond physical growth. A child may improve by engaging in physical activities physically, intellectually, socially and emotionally. The increasing use of technology, classrooms, and daycare centers on mental and non-physical activities led to reduced children's movement.

Figure 1 illustrates the essential benefits of physical education. It includes attributes like critical thinking, self-confidence, physical fitness, team player attitude, and goal setting attitude. Critical thinking is a significant benefit to the physical education system. It helps the students to widen their thinking capabilities. The creative thinking ability of children is broadened when they involve in physical activities. Besides, the physical activities also enable the children to apply their critical thinking ability for solving problems. The next main benefit is the increase in self-confidence. Physical education helps to boost the confidence level of the students. The increased confidence level aids them in facing real-time situations. It also enables the children to attend the assessment exams with more confidence. The other main benefit of physical education is physical fitness. The children become physically fit when they engage themselves in physical actions. There are many ways to improve, praise, empathy and understanding. In recent years one approach has fallen apart, although extremely effective: physical education. The physical education is also seen as an optional training and is not often taken seriously by students. However, the physical activity from this class may have a significant effect on the self-esteem of students. Although the daily activity has several positive results, they will look at three ways in which physical education can help boost the self-esteem of students: to promote skill feeling, to build up the skills of the teamwork, and to improve physiology and health.

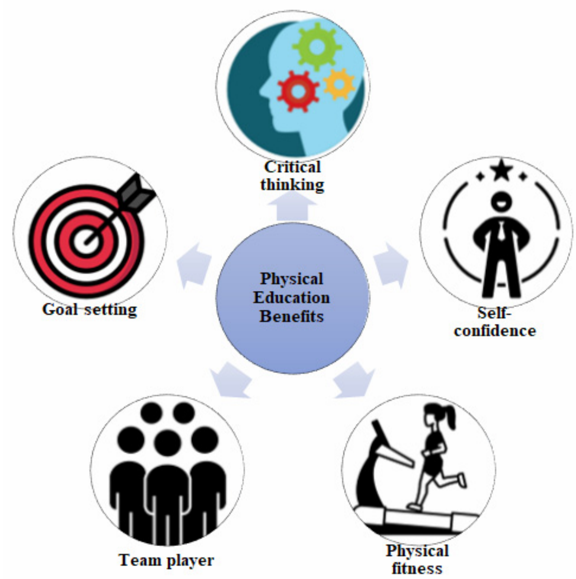

Figure 1. Physical education system benefits

Moreover, the increase in physical fitness increases their immunity levels that increase their resistance against various diseases—physical fitness further aids in improving the children's mental strength. Physical education helps to increase their performance as a team player. A team player attitude allows them to make decisions by consulting with other children. Leadership ability is another principal advantage of physical education. When the children undergo physical activities as a team, they also get a chance to face leadership responsibilities that help them make decisions and coordinate with their team members. Goal setting is yet another advantage of the physical education system. Goal setting capability allows the children to define a particular goal and work for it until the goal is attained. This helps the children to improve their mental skills as well. Daily activity leads to improving basic movement skills for your child, i.e. physical literacy. Besides promoting healthy physical activity, bone, muscle, heart and lungs will help develop healthy bones. Physical exercise allows your child to maintain healthy body weight as well. If you have signs of depression or anxiety or even a day off, physical activity might be the last thing. Physical exercise can, however, contribute significantly to mental well-being. "Feel-good" chemicals in the brain, known as endorphins, are released into the brain and help to boost mood, energies and sleep. Together, the positive effects lead to increased self-confidence and strength, even better-sleeping children that become involved every day.

3.2 Pillars of Physical Education in Modern Education System

Today physical education is an essential part of the educational curriculum. The physical education system is digitized using various modern aspects like the Internet of Things (IoT), wearable sensors, vision sensors, computational assessments, and machine learning algorithms.

Figure 2 shows the pillars of physical education in the modern education system. The first main pillar is the IoT. IoT utilizes the internet network for continuous monitoring of children when they perform physical activities. This enables the physical trainers to continuously evaluate the children's performance so that instruction can be given to improve their physical fitness. Wearable sensors are the devices worn by individuals like the accelerometer sensor, magnetometer sensor, skin conductance sensor, etc., that continuously capture the individuals' data. The collected data can be transmitted using wireless techniques like Bluetooth, Zigbee, Wi-Fi, etc. The collected data can be processed to infer useful information about the performance of the children. Like wearable sensors, vision sensors like Kinect sensors, RGB cameras, infrared cameras, etc., can be used to collect information about the children's physical activities. The vision sensors are more suitable for indoor activities, and wearable sensors are ideal for outdoor activities.

Assessment of the collected data is an essential aspect of physical education. Examination yields beneficial results that show the performance of the students. Based on the students' performance, the trainers set new targets so that the children can aim towards the goals for the betterment of their physical and mental states. A high-quality physical fitness program encourages all the students to enjoy several

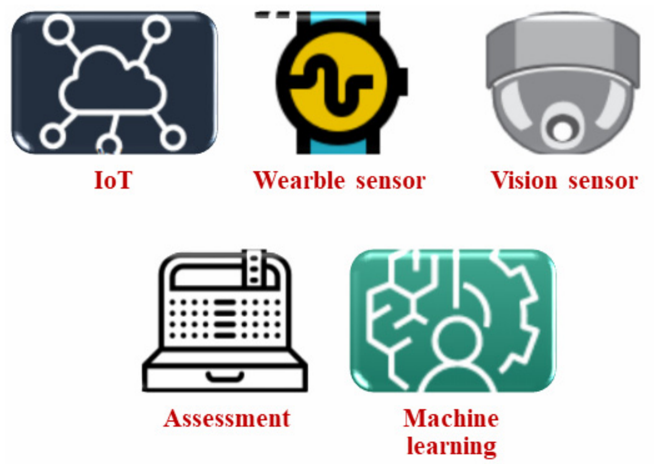

Figure 2. Pillars of physical education in modern education system

biological activities and excel in them. It builds some skills and the ability to use techniques, methods and compositional ideas effectively. As a result, they gain trust and learn about the importance of safe, active lives. In this way, they engage in various physical activities. Physical activity and physical exercise's cognitive advantages are not unilateral and are unique to the form, timing, and intensity of physical activity. Physical activity with the highest power can have the most significant gains; however, these outcomes are not necessarily transferable to significant interventions across many students. Machine learning algorithms are used for classifying the physical activities of the students. The classified activity and the action duration can be used to evaluate each student's intensity of physical action. The evidence indicates that increasing physical activity and health can boost academic performance and promote intellectual understanding of a school devoted to the recession, physical education and physical activities. Academic success is dependent on executive function and brain health. Care and memory cognitive essential functions make learning more straightforward, and these functions are improved by physical activity and higher aerobic fitness.

3.3 Physical Action Recognition Using IoT

IoT plays a significant role in the recognition of physical action without continuous physical monitoring of the trainer. The activity details can be transferred to the cloud using a wireless medium, and based on the transferred data, the processing is done to infer the student's actions.

Figure 3 shows the framework of physical activity recognition using IoT. The first component is the acquisition of action data from the student using wearable sensors. An accelerometer sensor is used for acquiring motion data. The tri-axial accelerometer captures the acceleration values along the x, y, and z-axis. In addition to the accelerometer sensor, wearable wrist pulse oximeter sensor and temperature sensors are used to monitor oxygen level, pulse rate, and the students' temperature when they perform physical actions. These data are transferred to the cloud using the IoT module. The transferred data are then processed in the server. Based on the accelerometer signal, the action performed by the student is inferred. This inferred action is transmitted to the mobile of the physical activity trainer. In addition to the concluded story, the values of oxygen level, pulse rate, and temperature of the student at various instants of time are also updated to the physical activity trainer. Fitness testing is a perfect way to track and evaluate students' potential to be fit, strong and agile with aerobics. It can enable students to understand how they are balanced and learn to set goals to enhance their fitness. Incorporate your everyday lessons and physical education curriculum health education and routine practice. Fitness education covers fitness elements, concepts of training, physical activity forms, and impacts on performance and overall health. Fitness assessments help students determine where they are and prepare for where they want to be in the future. Increased outcomes are obtained by rational decision-making. It allows students to be conscious of and practice good behaviours and find sustainable performance and development pathways. Minimize fitness test competition to ensure reliability, the assessments must be individual, and every student must obtain the same fitness test.

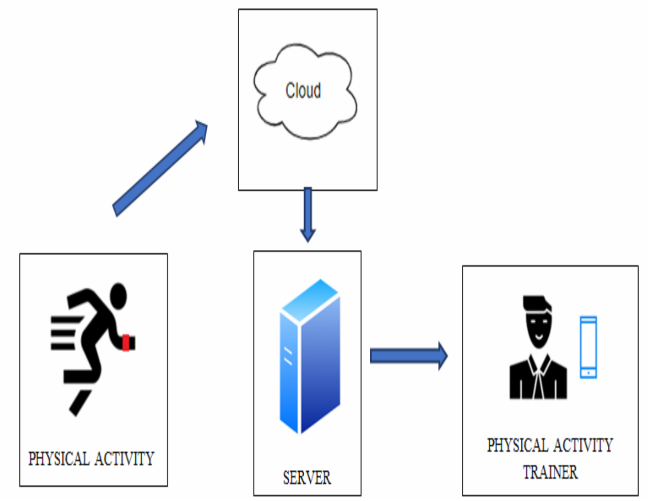

Figure 3. The framework of physical activity recognition using IoT

Figure 4 shows the screenshot of action recognition details in the mobile phone of the physical activity trainer. The details displayed on the first page includes student's name, class, a section of the student, activity recognized, and action duration. These details indicate the different types of actions performed and the period for which steps are completed. This gives knowledge to the trainer about the physical fitness of the students. Students can establish a hobby that preserves their physical health for their entire life. Increases energy and confidence Laziness is an unfit body companion. Fitness keeps you still active, energetic and healthy; it allows working and producing outcomes with greater competence and efficiency. It represents the ultimate trust level that increases, Physically fit, the personality is reworked. It enables you to do yourself without exhausted or impatient physical activities. Children get fit mentally and stress-free. It is time for children to play sports and participate in physical activity to have happiness, peace, and happiness.

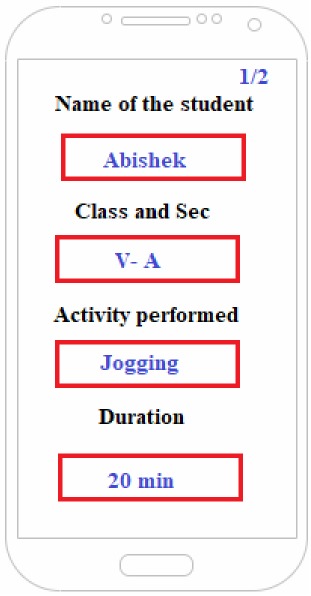

Figure 4. Screenshot of action recognition details

Figure 5 shows the screenshot of the medical parameter details in the physical activity trainer's mobile phone. These medical parameters include oxygen level in the blood, pulse rate, and temperature of the student. In case of any abnormal values in the medical parameters, the instructor instructs the students to stop the physical activity. Thus, IoT enables the integration of various medical and motion parameters.

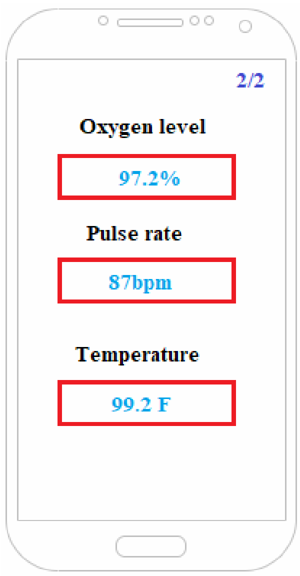

Figure 5. Screenshot of medical parameter details

3.4 Proposed IoT-based Physical Activity Recognition (IPAR) Model

In this research, we have proposed a novel IoT-based physical activity recognition model. The proposed model is given in Figure 6.

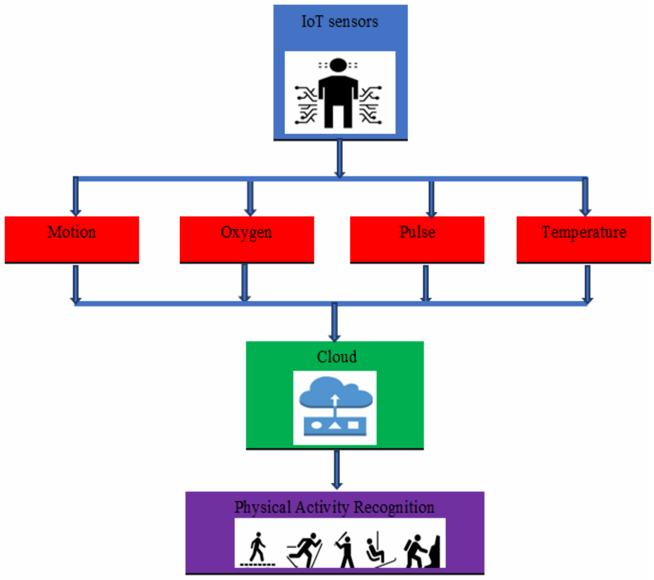

Figure 6. Proposed IoT-based physical activity recognition model

Figure 6 illustrates the proposed IPAR model. According to this model, various IoT sensors capture the students' motion and medical signals when they perform physical activities. These signals include motion signals from the accelerometer, oxygen level, pulse rate, and temperature. The captures signals are transferred to the cloud. From the cloud, the data is transferred to sever for processing. Processing of data involves recognition of physical activity. The recognized activity and the duration of action, and the medical parameters are then transferred to the instructor's mobile phone using an IoT network. Children's physical action recognition is performed by determining physical activity label (PAL)using the proposed Algorithm 1.

Algorithm 1. Proposed IoT-based physical activity recognition (IPAR) algorithm

Input:

Motion data along the x-axis $A_x = \{x_1, x_2, ..., x_n\}$.

Motion data along the y-axis $A_y = \{y_1, y_2, ..., y_n\}$.

Motion data along the z-axis $A_z = \{z_1, z_2, ..., z_n\}$.

Initialization:

Physical activity label $pal = 0$

Steps:

Compute Haar wavelet coefficients for every axis ($\phi_X^H, \phi_Y^H, \phi_Z^H$) using the following wavelet function

$$\phi_{X,Y,Z}^H(t) = \begin{cases} 1 & ; 0 \le t < 1/2 \\ -1 & ; 1/2 \le t < 1 \\ 0 & ; o.w \end{cases}.$$

Compute the feature vector as $f = [\phi_X^H \| \phi_Y^H \| \phi_Z^H]$.

Define the overall feature matrix as

$F = \{F_W | F_J | F_F | F_H | F_T\}$.

Form a single shared dictionary SD using

$$SD = \arg\max_{SD} \sum_{i=1}^{N} \max_{F}[P(F_i, \alpha / SD)].$$

Compute sparse coefficient matrix using

$\alpha = \min \|\alpha\|_0 \; s.t. \|F - SD * \alpha\| \le \xi$.

Divide the sparse coefficient matrix based on several classes C as $\alpha = \{\alpha_W | \alpha_J | \alpha_F | \alpha_H | \alpha_T\}$.

Compute the energy of each sub-sparse coefficient matrix using $E_i = \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_i^2(m,n)$.

Physical activity label is computed as

$pal = \arg\max_i E_i$.

Output:

Physical activity label pal .

Initially, the motion data along each axis is segmented using a window size of 1s. Let us consider the number of instances in each window as n. Features are extracted from this segmented data. In our work, a Haar wavelet transform is applied for the extraction of physical activity features. The wavelet function used for the generation of Haar features is given by

$$\phi_{X,Y,Z}^H(t) = \begin{cases} 1 & ; 0 \le t < 1/2 \\ -1 & ; 1/2 \le t < 1 \\ 0 & ; o.w \end{cases} \quad \textbf{(1)}$$

Here, t refers to the time interval and $\phi_{X,Y,Z}^H(t)$ refers to the Haar wavelet function for the x, y, and z-axis. Haar function produces an amplitude of unity whenever the time interval is between zero to half and amplitude of negative unity when the interval is between half and one. For the remaining intervals, it produces an amplitude of zero. Using the generated Haar wavelet coefficients, compute the feature vector as

$$f = [\phi_X^H \| \phi_Y^H \| \phi_Z^H] \quad \textbf{(2)}$$

The Haar wavelet coefficients along the x-axis are the Haar wavelet coefficients along the y-axis and are the Haar wavelet coefficients along the z-axis. Further f is the concatenated feature vector formed by joining the Haar wavelet coefficients along the x-axis, Haar wavelet coefficients along the y-axis, and Haar wavelet coefficients z-axis. The overall feature matrix is formed using

$$F = \{F_W \,|\, F_J \,|\, F_F \,|\, F_H \,|\, F_T\} \quad \textbf{(3)}$$

The above equation F_W refers to the features of walking action, F_J refers to the wavelet features of jogging action, F_F refers to Frisbee action's wavelet features, F_H hopping action features, and the tennis game features. Further F is the overall feature matrix. This matrix is formed by concatenating wavelet features of walking action, jogging action, Frisbee action, hopping action, and tennis game. The next step is to develop a single shared dictionary SD using,

$$SD = \arg\max_{SD} \sum_{i=1}^{N} \max_{F_i}[P(F_i, \alpha / SD)] \quad \textbf{(4)}$$

Here, the term $[P(F_i, \alpha / SD)]$ refers to the probability of the feature matrix occurrence for the sparse coefficient matrix α given the shared dictionary *SD*. The term $SD = \sum_{i=1}^{N} \max_{F_i}[P(F_i, \alpha / SD)]$ refers to the total sum of the feature matrix arguments F_i that produces maximum values of probability $[P(F_i, \alpha / SD)]$.

The next step is to compute the sparse coefficient matrix using

$$\alpha = \min \|\alpha\|_0 \;\; s.t. \|F - SD * \alpha\| \le \xi \quad \textbf{(5)}$$

Here α is the sparse coefficient matrix and $\|\alpha\|_0$ refers to the total number of non-zero elements in this matrix. The aim is to minimize the l0 norm such that the values $\|F - SD * \alpha\|$ are within the error limit. The error limit is referred to as ξ. In this work, we have fixed the error limit as 0.01. The generated sparse coefficient matrix is divided based on the number of class C as

$$\alpha = \{\alpha_W \,|\, \alpha_J \,|\, \alpha_F \,|\, \alpha_H \,|\, \alpha_T\} \quad \textbf{(6)}$$

Here, α_W refers to the sparse coefficient matrix of walking action, α_J refers to the sparse coefficient matrix of jogging action, α_F refers to the sparse coefficient matrix of frisbee action, α_H and is the sparse coefficient matrix of hopping action α_T is the sparse coefficient matrix of the tennis game. The energy of each sub-sparse coefficient matrix is then computed using

$$E_i = \sum_{m=1}^{M} \sum_{n=1}^{N} \alpha_i^2(m,n) \quad \textbf{(7)}$$

The square of each coefficient in the sparse coefficient matrix is the sum of the square of all the coefficients of the sparse coefficient matrix and E_i is the energy of each physical action. The value of I ranges from 1 to 5 and refers to each of the five physical actions. Finally, the physical activity label is computed as

$$pal = \arg\max_i E_i \quad \textbf{(8)}$$

The physical activity label is computed as the argument of i that produces a maximum value of energy E_i.

3.5 Benefits of IPAR System

The proposed IPAR framework has various advantages. Since this framework is based on IoT, it enables online monitoring of students' physical activities by the trainers through their mobile phones. This helps the trainers to guide the students. The application of IoT in the physical education system dramatically enhances the physical education curriculum by constantly recognizing physical activities and monitoring medical parameters like oxygen level, pulse rate, and temperature.

4 Results and Discussion

4.1 Evaluation of Physical Activity Recognition Performance

The performance of the proposed physical activity recognition system was evaluated using various classification algorithms. Here five different actions were considered: walking, jogging, Frisbee, hopping, and tennis.

To validate the system's overall performance using the proposed IoT-based physical activity recognition (IPAR) algorithm, we have compared algorithms like Naïve Bayes, k-NN, random forest, and artificial neural network (ANN), and the proposed IPAR algorithm.

Table 1 shows that the proposed IPAR algorithm's performance is outstanding compared to other algorithms like Naïve Bayes, k-NN, random forest, and ANN. Naïve Bayes produces an accuracy of 85.93%, k-NN produces an accuracy of 88.74%, random forest produces an accuracy of 90.74, ANN produces an accuracy of 91.74%. The proposed IPAR attained an accuracy of 95.82%. The main reason behind the attainment of higher accuracy in the proposed system is energy usage as a metric to quantify the amount of content possessed by each action in the sparse coefficient matrix.

Table 1. Comparison of overall accuracy

Classification algorithms	Overall accuracy (%)
Naïve Bayes	85.93
k-NN	88.74
Random Forest	90.74
ANN	91.74
IPAR	95.82

Figure 7 shows the comparison of specificity for various classification algorithms. From Figure 7, we infer that the value of specificity for the classification of 5 action classes using the Naïve Bayes algorithm is 85.23%. The K-NN classifier produces a specificity of 89.98%; random forest achieves a rate of 90.75%, ANN produces a specificity of 93.12%. The proposed classifier performs a rate of 96.32%. The proposed classifier achieved the highest specificity because it utilizes a sparse representation theory to represent each action class. This representation aids in the compact representation of the action class in a discriminant manner and hence produces robust recognition results.

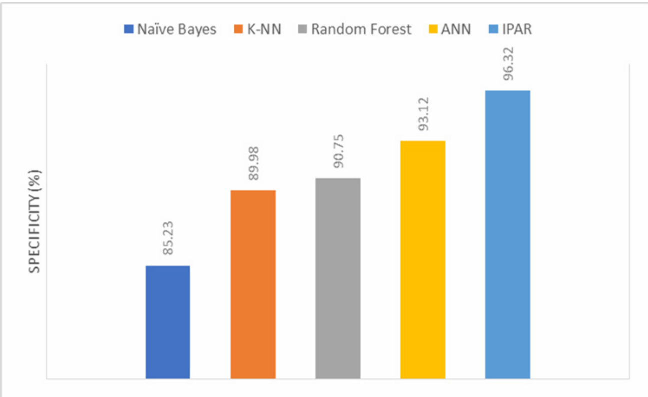

Figure 7. Comparison of specificity

Figure 8 shows the comparison of precision for various classification algorithms. From Figure 8, we infer that the value of accuracy for the classification of 5 action classes using the Naïve Bayes algorithm is 89.79%. The K-NN classifier produces a precision of 90.86%; random forest achieves a rate of 92.32%, ANN delivers an accuracy of 95.42%. The proposed classifier performs a rate of 96.95%. The attainment of 96.85% precision is because of the computation of probability $[P(F_i, \alpha / SD)]$. This component produces the highest probability of the occurrence of action class with label i.

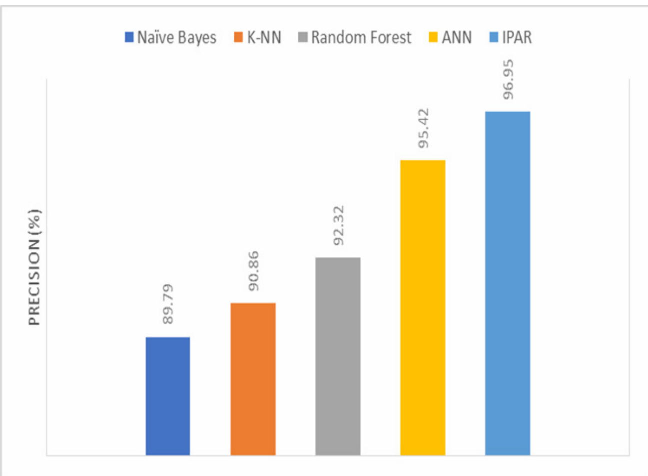

Figure 8. Comparison of precision

Figure 9 shows a comparison of recall for various classification algorithms. From Figure 9, we infer that the value of recall for the classification of 5 action classes using the Naïve Bayes algorithm is 87.54%. The K-NN classifier produces a recall of 91.46%; random forest achieves a rate of 92.23%, ANN makes a recall of 94.35%. The proposed classifier performs a rate of 95.63%. The IPAR system achieves the highest recall as its sensitivity to discriminate from one class to another increase. This is because the IPAR system considers individual actions independently and computes the correlation between various actions.

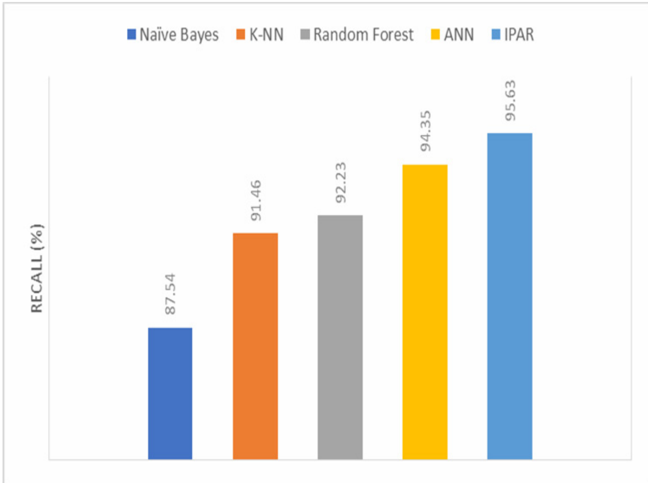

Figure 9. Comparison of recall

Figure 10 shows the comparison of the F-score for various classification algorithms. From Figure 10, we infer that the F-score value for the classification of 5 action classes using the Naïve Bayes algorithm is 88.93%. The K-NN classifier produces an F-score of 91.42%, random forest achieves 93.85%, and ANN creates an F-score of 94.83%. The proposed classifier performs a rate of 97.83%. Our proposed IPAR classifier achieves the highest F-score due to Haar wavelet coefficients' usage that produces representative action features.

Figure 10. Comparison of F-score

4.2 Computational Time Comparison

Computational time comparison is done by computing the time to recognize one physical action by the server. The server was loaded with other machine learning algorithms, and the average time for classifying one action was computed.

Table 2 shows a comparison of time complexity. From Table 2, we see that the Naïve Bayes classifier used an average time of 93.13ms. The k-NN uses a computational time of 84.24ms. The random forest classifier uses a time of 100.46ms. ANN uses the time of 83.28ms. IPAR system uses a time of 53.96ms. We infer that the time complexity of the proposed method is the minimum. This is because we have utilized the sparse representation theory that computes the sparse coefficients quickly and efficiently.

Table 2. Comparison of computational time

Classification algorithms	Average computational time (ms)
Naïve Bayes	93.13
k-NN	84.24
Random Forest	100.46
ANN	83.28
IPAR	53.96

5 Conclusion and Future Work

This paper has proposed a new scheme for physical activity recognition using the Internet of Things called the IoT-based Physical Activity Recognition (IPAR) model. In this framework, the accelerometer signal was initially captured using the school students' wearable motion sensor device. The data captured by the sensor is continuously transferred to the cloud. From the cloud, this data is transferred to the servers where the action recognition is performed. The recognized actions were continually updated to the instructors to monitor the students' performance using the IoT framework continuously. The proposed action recognition scheme produced robust and reliable results. The IPAR algorithm attained a specificity value of 96.32%, a precision of 96.95%, and a 95.63% recall. In the future, we plan to design a new mobile application that physical education trainers can use for monitoring the students.

References

[1] D. Kahan, T. L. McKenzie, Website Representations of Physical Education and Physical Activity: Comparison of Public Charter and Private Schools, *Research quarterly for exercise and sport*, pp. 1-8, July, 2020.

[2] M. Abdel-Basset, G. Manogaran, M. Mohamed, E. Rushdy, Internet of things in smart education environment: Supportive framework in the decision-making process, *Concurrency and Computation Practice and Experience*, Vol. 31, No. 10, Article No. e4515, May, 2019.

[3] A. J. Maher, H. Fitzgerald, The culture of special schools: perceptions of the nature, purpose and value of physical education, *Educational Review*, February, 2020.

[4] X. Xu, D. Li, M. Sun, S. Yang, S. Yu, G. Manogaran, G. Mastorakis, C. X. Mavromoustakis, Research on key technologies of smart campus teaching platform based on 5G network, *IEEE Access*, Vol. 7, pp. 20664-20675, January, 2019.

[5] R. Coffey, J. A. Haegele, X. Zhu, J. Bobzien, Examining physical education experiences at integrated and residential schools for students with visual impairments, *British Journal of Visual Impairment*, Vol. 38, No. 3, pp. 312-323, September, 2020.

[6] F. Niaz, M. Khalid, Z. Ullah, N. Aslam, M. Raza, M. K. Priyan, A bonded channel in cognitive wireless body area network based on IEEE 802.15.6 and internet of things, *Computer Communications*, Vol 150, pp. 131-143, January, 2020.

[7] R. Bowles, M. O'Sullivan, Opportunity knocks: the intersection between schools, their teachers and external providers of physical education and school sport, *Discourse*, Vol. 41, No. 2, pp. 251-267, February, 2020.

[8] A. Prathik, K. Uma, J. Anuradha, An Overview of application of Graph theory, *International Journal of ChemTech Research*, Vol. 9, No. 2, pp 242-248, 2016.

[9] B. D. Kern, D. W. Ellison, C. M. Killian, F. Widmer, Initial Validation of the Teaching Sustainability Questionnaire and Relationships of Latent Factors Predicting Physical Education Teachers Intent to Remain Working in High Poverty Schools, *Measurement in Physical Education and Exercise Science*, Vol. 24, No. 3, pp. 181-193, 2020.

[10] G. Manogaran, S. Baskar, P. Shakeel, N. Chilamkurti, R. Kumar, Analytics in real time surveillance video using two-bit transform accelerative regressive frame check, *Multimedia Tools and Applications*, Vol. 79, No. 23-24, pp. 16155-16172, June, 2020.

[11] Y. V. Nieto, V. Garcia-Diaz, C. E. Montenegro, Decision-making model at Higher Educational Institutions based on Machine Learning, *Journal of Universal Computer Science*, Vol. 25, No. 10, pp. 1301-1322, October, 2019.

[12] Y. Nieto, V. Gacia-Diaz, C. Montenegro, C. C. Gonzalez, R. G. Crespo, Usage of Machine Learning for Strategic Decision Making at Higher Educational Institutions, *IEEE Access*, Vol. 7, pp. 75007-75017, May, 2019.

[13] S. Frydendal, L. F. Thing, A shameful affair? A figurational study of the change room and showering culture connected to physical education in Danish upper secondary schools, *Sport, Education and Society*, Vol. 25, No. 2, pp. 161-172, 2020.

[14] M. J. Duncan, C. M. P. Roscoe, M. Noon, C. C. T. Clark, W. O'Brien, E. L. J. Eyre, Run, jump, throw and catch: How proficient are children attending English schools at the fundamental motor skills identified as key within the school curriculum, *European Physical Education Review*, Vol. 26, No. 4, pp. 814-826, November, 2020.

[15] S. Beni, D. Ní Chróinín, T. Fletcher, A focus on the how of meaningful physical education in primary schools, *Sport, Education and Society*, Vol. 24, No. 6, pp. 624-637, 2019.

[16] S. Vazou, A. Mischo, M. A. Ladwig, P. Ekkekakis, G. Welk, Psychologically informed physical fitness practice in schools: A field experiment, *Psychology of Sport and Exercise*, Vol. 40, pp. 143-151, January, 2019.

[17] D. Barker, In defence of white privilege: physical education teachers' understandings of their work in culturally diverse schools, *Sport, Education and Society*, Vol. 24, No. 2, pp. 134-146, 2019.

[18] Q. G. To, L. Wharton, D. Gallegos, M. Stylianou, D. V. Do, K. G. To, H. T. M. Tran, S. G. Trost, School-based physical education: Physical activity and implementation barriers in Vietnamese elementary schools, *European Physical Education Review*, Vol. 26, Article No. 2, pp. 587-606, May, 2020.

[19] R. M. Telford, L. S. Olive, R. J. Keegan, S. Keegan, L. M. Barnett, R. D. Telford, Student outcomes of the physical education and physical literacy (PEPL) approach: a pragmatic cluster randomized controlled trial of a multicomponent intervention to improve physical literacy in primary schools, *Physical Education and Sport Pedagogy*, Vol. 26, No. 1, pp. 97-110, 2021.

[20] A. Quintas, J. C. Bustamante, F. Pradas, C. Castellar, Psychological effects of gamified didactics with exergames in Physical Education at primary schools: Results from a natural experiment, *Computer and Education*, Vol. 152, Article No. 103874, July, 2020.

[21] R. M. Telford, L. S. Olive, R. J. Keegan, S. Keegan, R. D. Telford, Teacher and school outcomes of the Physical Education and Physical Literacy (PEPL) approach: a pragmatic cluster randomized controlled trial of a multicomponent intervention to improve physical literacy in primary schools, *Physical Education and Sport Pedagogy*, Vol. 26, No. 1, pp. 79-96, 2021.

[22] J. S. Borgen, B. O. Hallås, K. Løndal, K. M. Moen, E. G. Gjølme, Problems created by the (un)clear boundaries between physical education and physical activity health initiatives in schools, *Sport, Education and Society*, Vol. 26, No. 3, pp. 239-252, 2021.

[23] T. Bopp, M. Stellefson, Practical and ethical considerations for schools using social media to promote physical literacy in youth, *international Journal of Environmental Research and Public Health*, Vol. 17, No. 4, Article No. 1225, February, 2020.

[24] L. Wang, J. Qi, Effect of student-related factors on their attitudes towards peers with disabilities in physical education: evidence from elementary schools in China, *Asia Pacific Journal of Education*, Vol. 40, No. 2, pp. 143-153, 2020.

[25] C. Burnett, A national study on the state and status of physical education in South African public schools, *Physical Education and Sport Pedagogy*, Vol. 26, No. 2, pp. 179-196, 2021.

[26] J. Mangione, M. Parker, M. O'Sullivan, M. Quayle, Mapping the landscape of physical education external provision in Irish primary schools, *Irish Educational Studies*, Vol. 39, No. 4, pp. 475-494, 2020.

[27] T. Fletcher, J. Lorusso, J. Halas, Redesigning physical education in Canada, in: H. A. Lawson (Eds.), *Redesigning Physical Education*, Routledge, 2018.

Biographies

Lixun Hu receivd the M.S. degree in athletic training from Xi'an Physical Education University, in 2005 and 2008. In August 2006, he attended the International Olympic Forum for PE post-graduates all over the country held by Beijing Sport University, and received the certificate of completion. He was a Visiting Scholar with The University of Utah, USA. He is currently an associate professor in Shaanxi University of Chinese Medicine. His research interests include athletic training, traditional health care sports, integration of sports and medicine, and he has a great number of publications in his research related fields.

Caili Liu receivd the M.S. degree in University of Electronic Science and Technology in 2009 and 2012. She is currently a senior computer engineer in Xi'an International University. Her research interests include computer and communication security, big data technology, data mining and she has a great number of publications in her research related fields.

Korhan Cengiz received the BS degrees in Electronics and Communication Engineering from Kocaeli University, Turkey in 2008. He took his PhD degree in Electronics Engineering from Kadir Has University, Turkey in 2016. Since 2018, he has been an Assistant Professor in Electrical-Electronics Engineering, Trakya University, Turkey. Dr. Cengiz is the author of over 40 articles including IEEE Internet of Things Journal, IEEE Access, Expert Systems with Applications, Knowledge Based Systems and ACM Transactions on Sensor Networks. His research interests include wireless sensor networks, wireless communications, statistical signal processing, indoor positioning systems, internet of things, artificial intelligence and 5G.

Gunasekaran Nallappan received the Ph.D. degree in mathematics from Thiruvalluvar University, Vellore, India, in 2018. He is currently working as a Postdoctoral Research Fellow with the Computational Intelligence Laboratory, Toyota Technological Institute, Nagoya, Japan. He has authored or co-authored more than 50 research articles in various SCI journals. His research interests include complex-valued NNs, complex dynamical networks, control theory, stability analysis, sampled-data control, multi-agent systems, T-S fuzzy theory, and cryptography. He serves as a reviewer for various SCI journals.