

A Multi-level Fusion System for Intelligent Capture and Assessment of Student Activity in Physical Training based on Machine Learning

Mustafa Altaee^{1*}, A. Jawad², Mohammed Abdul Jalil^{3,4}, Sanaa Al-Kikani⁵, Ahmed Oleiwi⁶, Hatira Günerhan⁷

¹Department of Medical Instruments Engineering Techniques, Alfarahidi University, Baghdad, Iraq,

²Department of Computer Communications Engineering, National University of Science and Technology, Thi Qar, Iraq, ³Department of Computer Engineering Techniques, Alturath University College, Baghdad, Iraq,

⁴MEU Research Unit, Middle East University, Amman 11831, Jordan, ⁵Department of Physical Education and Sport Science, Al Mustaqbal University College, 51001 Hilla, Babylon, Iraq, ⁶Department of Biomedical Engineering, College of Engineering, University of Warith Al-Anbiyaa, Karbala, Iraq, ⁷Department of Mathematics, Faculty of Education, Kafkas University, Kars, Turkey

Emails: m.altaee@alfarahidiuc.edu.iq; a.jawad@nust.edu.iq;

mohammedjalil24@gmail.com; dr.sanaa@uomus.edu.iq; a.oleiwi@uowa.edu.iq; hatira.gunerhan@kafkas.edu.tr

Abstract

To record and evaluate students' physical education (PE) class participation, this study proposes using machine learning aided physical training framework (ML-PTF). Improve student achievement in PE with the help of the Multi-level Fusion System that employs machine learning strategies. The system integrates sensor data, video data, and contextual data to deliver a holistic and precise evaluation of student engagement. This study's simulation analysis shows that the ML-PTF improves the reliability of evaluating universities' PE programs. A important reference path and paradigm for advancing tertiary-level PE for graduates, the multi-level fusion system also provides an investigation of information technology and language education integration. The experimental findings demonstrate that the ML-PTF is superior to other approaches in terms of learning rate, f1-score, precision, and probability, as well as student engagement, involvement, and recognition accuracy.

Received: January 17, 2023 Revised: April 02, 2023 Accepted: June 02, 2023

Keywords: Physical Education; Machine Learning; A Multi-level Fusion System; Assessment Model; Student Activity Prediction

1. Introduction

Higher education institutions can benefit from implementing a multi-level fusion system into their physical education (PE) programs [1]. To provide a thorough and precise evaluation of student activity in PE programs, the system integrates data from a variety of sources and levels, including sensor data, video data, and contextual data [2-4]. College students benefit greatly from participating in PE classes because of the many transferable skills they learn and the healthy habits they adopt. Student achievement and social skills, such as collaboration and teamwork, can both benefit from participation in sports. Excellent college PE programs provide students the chance to try new sports and teach them how to use new strategies and ideas in their own lives and classrooms. Sports and physical exercise motivate group cohesion, leadership, and problem-solving abilities, and they complement academic learning [5-7]. Therefore, a multi-level fusion system can improve the precision with which colleges assess the quality of PE instruction and offer a model for designing post-secondary PE courses [8-10].

Team sports promote mentoring among older players, younger players, trainers, and athletes [11]. Players with supportive mentors are much more likely to follow successful role models during their lifetime while they are young [12,13]. Soft skills are personal characteristics that enable people to have good social ties. Team sports are an excellent source for developing soft skills as they help athletes learn in an encouraging atmosphere [14,15]. Players are encouraged to convey their supervisor's and leader's concerns, expectations, and disappointments [16]. PE enables students to play quickly, and athletes build the skills they need to decide efficiently [17]. Team sports inspire players to do their best to assist a team member, and participants develop crucial decision-making skills to support them before or during the game [18]. A PE teacher's true long-term obligation is to instruct and encourage students to understand the entire safe lifestyle's value benefits. It will promote a balanced diet and outside-the-classroom events [19]. PE teachers play a leading role in the creation of sports programs. Teachers are often knowledgeable and responsible for encouraging this awareness of the range of physical exercise advantages [20]. PE teachers have an obligation to their pupils to nurture such attitudes [21]. The task description of the physical training instructor requires inspiration and support for students [22]. This means being sensitive to the needs and students and pushing us to work and achieve. Colleges and universities must find opportunities to help students learn physically rather than necessarily imposing a curriculum [23].

Machine learning in education is a form of personalized learning that can be used for each student's educational experiences. Machine learning-based PE for students is led here to follow the pace they want and decide [24-26]. Machine learning is an artificial intelligence (AI) sub-set that lets computers or machines learn from all past data and make smart choices. The machine learning system includes capturing, maintaining, and transforming rich information into an organized base of expertise for multiple uses in different fields. In the educational sector, teachers can save time using machine learning for easier student performance assessment in physical training. Objective performance evaluation of a student is essential for thorough research of elite sports. The automatic identification and recognition of sports movements surpass the restrictions of manual performance measurement techniques.

The main contributions of this study are:

- i. Designing machine learning assisted physical training framework (ML-PTF) has been proposed to evaluate a multi-level fusion system student performance and assesses student activity in the PE classroom
- ii. Analysis of the teaching quality in physical training improves the student's physical health
- iii. The simulation results have been performed, and the ML-PTF proposed a method to enhance health outcomes and increase student attention levels in PE.

The entire structure of the study: Section 1 summarizes the basic knowledge on machine learning-based college student physical activity (PA) prediction, and Section 2 literature study. Section 3 proposed ML-PTF to predict student activity and analyze the teaching quality. Section 4 elaborates on the numerical results and discussion. Section 5 concludes the overall paper's performance.

2. Literature Review

This section includes the most significant research models among the extensive literature survey performed as the pilot study. The reports of them are summarized below with valid points.

Tao *et al.* [27] suggested the quality of life (QoL) assessment model for college students for self-determined motivation. To better promote the PA and QoL of university students, they considered the correlations between PA and self-determined motivation and the perceived competence of this population. The results showed that the perceived skills were important in making decisions and decisions relevant to PA and improved the quality of education in Chinese students. Furthermore, similar techniques were developed to inspire Chinese university students to participate in PA.

Kim and Cardinal [28] discussed PA education (PAE) for university students' motivation. This research investigated the differences between universities with various PAE policies in PA encouragement, skill, and weekly exercise in metabolism equivalent units. This study's findings showed that having a required PAE policy could help more students with a less autonomous incentive to be met than the optional PAE policy. This result emphasized that the potential to reach less enthusiastic students could be a primary advantage of having the required PAE policy.

Solis *et al.* [29] described the adolescents' motivational processes and satisfaction with life. A regressive structural equation modeling analysis showed two theoretical lines: Positive and negative, positively and positively correlated. The findings demonstrated the significance of incentive pathways for PA and PA's effects on physical health and teenagers' PA.

Field programmable gate arrays (FPGA)-based adaptive data reinforcement technique (ADRT) platform for sports course management system discussed by Pan [30]. The growth of IT and expanded activities in PE courses were

significant criteria for the students. This thesis suggested an ADRT technology and claimed that the best approach, when paired with an integrated data protection technique based on FPGA, is the singular run-time rebuild. Management capabilities in-game boosted human efficiency, gave clients a benchmark for reforming the physics curriculum in university physics training, and was instrumental in in-game physics training.

Machine learning-based physical fitness evaluation model (MLPFEM) for wearable running monitoring of teenagers deliberated by Guo *et al.* [31]. While the latest wearable products have good data acquisition capabilities on the market, their performance in useful information processing remains insufficient due to the lack of a proper computer model and extensive data analysis. This paper suggested a wearable running control system for adolescents based on the MLPFEM. A gradient boosting machine version was used along with a sophisticated selection of the characteristics and Bayesian hyperparameter optimization.

PA recognition and monitoring (PARM) model for PA recognition and health monitoring of college students was explored by Zhong [32]. This article's purpose was to track college students' PA. A secure, energy-efficient student monitoring system was created and built to allow health criteria to be submitted in real-time testing. Patient protection was constantly monitored using different sensors connected to PARMM and was considered a central paradigm of intelligent healthcare in the current framework. The experimental test results were validated based on current PARM networks that could address new university students' successful health supervision posed by IoT conditions.

Virtual reality system (VRS) for college PE expressed by Ding *et al.* [33]. University physical fitness is integral to public health programs and higher education. Promoting the scientific and current building of the education system in colleges and universities would improve higher education research and efficiency. Considering the problems of single education approaches, this paper designed and suggested a VRS consisting of the internet of objects, a cloud server, and a smartphone client built on VRS s with sufficient long-term teaching capabilities.

Section 2 explored the existing methods such as FPGA- ADRT, MLPFEM, PARMM, and VRS. This survey found some issues with the existing method, so in this article, ML-PTF has been proposed to overcome the issues. The ML-PTF has been proposed to reduce physical training risk factors based on continuously monitoring student activity.

3. ML-PTF for Students

This paper discussed a ML-PTF for college students to improve student physical health. PE specifically develops the talent to interact with others. It allows leadership and team skills to help students learn to experience other educational fields. Students are devoted to physical exercise, which offers authentic learning contexts. Students are challenged to improve their physical and interpersonal abilities. College students are empowered to participate in physical activities and consider how this affects their own and other's well-being. Hence in this paper, ML-PTF has been proposed to enhance health outcomes and improve team sports outcomes. This paper provides comprehensive research to improve teacher-level evaluation for the PE program in colleges to measure the teacher PE-learning effect in universities, from teacher skill and the student learning effect.

Figure 1 illustrates the characteristics of Physical Education (PE). The PE curriculum's primary goal is to facilitate students' acquisition of abilities, skills, and motivation within a health-conscious physical environment, ensuring their preparedness for higher education and professional pursuits. Students are encouraged to seamlessly blend cognitive, psychomotor, and affective principles, thereby fostering a comprehensive and culturally diverse outlook on the surrounding world through their active participation in the PE domain. The aspiration is for students to not only enhance their physical fitness but also acknowledge their role in promoting well-being through meaningful interactions. Consistent engagement in physical activities has been empirically linked to both mental and physical health benefits. However, there tends to be a significant decrease in exercise levels among experts, coinciding with a noticeable rise in obesity rates and related health issues. Fostering physical activity (PA) among experts presents an avenue to enhance overall well-being, particularly among those grappling with mental health conditions. The inclusion of university students in such programs assumes significance as it aids in sustaining interest in physical exercise following periods of illness and injury.

3.1. Learner agency

Through specialized education training, students learn to acquire their expertise by acquiring the techniques required to administer their health and physical fitness, gain movement skills, and achieve practical expectations to improve their

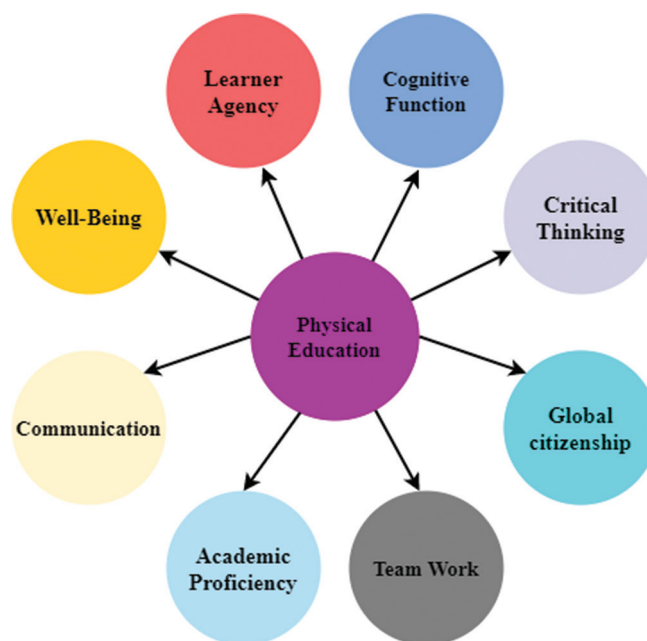


Figure 1: Physical education.

health and well-being. PE enables students to assess and sustain physical fitness in a health-related context by applying themselves to PA and assessing their character in physical exercise's health and personal performance.

3.2. *Academic proficiency*

PE teaches students social responsibility by engaging in physical exercises and the importance of physical activities for fitness, self-expression, and social interactions. Health education provides students with basic medical skills to manage physical, emotional, and social health. Critical skills build together in fitness and PE, supporting academic success and college preparedness.

3.3. *Global citizenship*

It focuses on the opportunity to collaborate concerning problem-solving. PE encourages children to conduct themselves and others' social responsibility when engaging in individual or teamwork. Students learn to embrace individual differences, participate in initiatives, address issues, and play games with classmates. Health education promotes efficient growth use in the daily life of reading and interpersonal contact skills. Students strive to resolve challenges and defend their personal needs respectfully and responsibly in health and PE.

3.4. *Cognitive function*

PE promotes academic achievement in all fields of substance. Students discover that holistic well-being is the cumulative state of their physical, physiological, and spiritual health. The creation of people with literature on health with expertise, abilities, and inspiration to make healthcare, disease prevention, and health promotion and decisions to maintain their QoL.

3.5. *Communication*

Health education teaches, practices, and evaluates the skills of communicating between students. Learning experiences encourage strong communication skills in relationships, self-promotion, face-to-face conversation, email, messaging, social media, or other technology. PE can allow students to choose, engage in, and allow for self-expression learning experiences. Students can be trained to welcome suggestions for performance improvement and create ways for peers to receive appropriate feedback.

3.6. *Critical thinking skills*

The growth of critical thought and problem-solving is supported by PE. In PE, students learn to assess the effects of personal well-being and use personal knowledge to take action to set targets for improving or maintaining physical

fitness. Health education teaches students seven key health skills, including factors analysis, accurate and credible information access, decision-making, setting targets, inter-personal contact, and self-management;

3.7. Well-being

Physical training improves people’s expertise and abilities to ensure personal well-being. Health and PE aim to teach students to control their physical, behavioral, emotional, and social fitness.

3.8. Team work

When individual team members coordinate their activities and collaborate toward a shared purpose, the most successful coordination occurs. Higher productivity, lesser internal conflicts, and a more enjoyable training experience are all benefits of effective teamwork. In general, it can result in improved choices and decisions. Communication, cooperation, balancing of participant contributions, collective assistance, effort, and stability are the six components of teamwork that determine teamwork effectiveness.

Figure 2 illustrates the machine learning-based Physical Education Teaching Model (ML-PETM), which aligns with the prescribed structure and instructional approach outlined in the teaching theory guidelines. This model serves to systematize the entirety of the teaching process and the interrelationships among various components from a broad perspective, emphasizing the practical implementation of the teaching model. Within this framework, the instructor imparts lessons and elucidates technical motions. Subsequent to the instructor’s presentation, students enhance their motor skills learning by observing and replicating the demonstrated actions. However, due to the limited duration of observation, students may struggle to fully grasp the nuances of the gestures. Teachers capture important movements in videos and label with slow motion or words the technical elements of movement to help them understand essential motion using contemporary education materials. The development of an ML teaching mode for PE is based on ML teaching theory. The benefits from conventional and online lessons are paired with a mixed physical approach by analyzing PE instruction features and the advancement of information technology. Teaching is divided into three interrelated parts: autonomous prior class learning, functional classroom learning, and complimentary expanded classroom learning.

The conventional teaching modus before training has been turned into a modern teaching method before training. Teachers will direct students during the entire teaching process to autonomously learn by teaching exercises, arranging teaching contents according to the students’ self-studies, and guiding students to consolidate each class’s content. In the course of independently preparing before the school, the instructor films the appropriate physical exercise tape prepares the training program, points out the associated questions, determines the learning objective, and passes it to

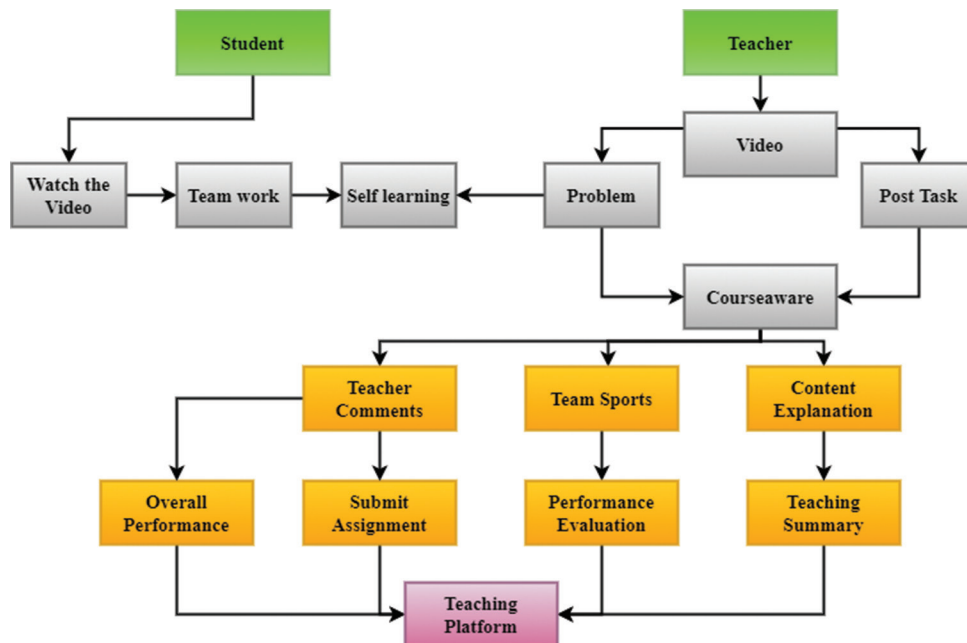


Figure 2: Machine learning-based a multi-level fusion system for physical education teaching model.

the teaching course material to interpret the learning condition. Through teaching platforms, students can find solutions to teacher issues through self-training, viewing teaching programs and videos, holding group discussions, and finding answers from teachers to online problems. Teachers have to lead and supervise students in the course of autonomous learning. Students blend the substance of autonomous learning with their interpretation and view it in communities in classroom instruction comments. The instructor answers students' questions, outlines the instructional material, and shows them according to the course's input. Students learn the contents in groups. Machine learning can track students' actions and engage with the students during the learning interaction. By analyzing students' success in the course, the teacher judgments the learning status of the students identifies each action of the students, compares them to standard measures in the machine library, assess the standardization of student activities, and directs them to help them complete the content of their teaching courses at the right time. The ML helps students adapt their academic attitudes and weakens their insecurity and apprehension with learning disabilities. The teachers will provide individual instructional instruction for each student through the ML record of every student's learning situation, learning development, and mastery of courses. During consolidation after class, students report and submit PE courses' contents to their study conditions. The instructor reflects on the videos of the students and notes the issues that arise. The students reflect and summarize the teacher's remarks and strengthen the existing issues. In addition, instructors can submit the course materials gathered to the educational website to observe their learning conditions to extend the course freely.

Data mining technology can effectively reduce the noise level of data collected in the education sector and useful information from the database, improving teacher evaluations of education skills and providing reliable bases for future educational progress. The teaching types of PE courses in colleges are diversified due to students' professional and personality variations. Some noise points include the actual appraisal of the teacher's ability to teach or even the inverse assessment of the teacher's ability to teach. It is impossible to remove interferences from noise points efficiently by manual processes. These methods are not possible for engineering applications, particularly when the number of noise points is high. Data mining technologies can efficiently eliminate noise from batches in machine learning and obtain useful information from a vast volume of data.

$$C_j = c_{j1}, \dots, c_{ji} \quad (1)$$

As deliberated in equation (1) cleaned data set has been defined. Where C_j denotes the j^{th} data set sample, c_{j1} is explores the first attribute sample vector C_j attribute value, and c_{ji} the first vector sample attribute C_j , meaning that the sample vector C_j Dimension is i . Therefore this equation explored the cleaned data in the PE teachers teaching ability.

A soft interval function, which requires a limited number of samples not to meet the restriction, is implemented further to increase data fault tolerance in equation (2):

$$Z^S C_j + a \geq \delta_j \quad (2)$$

As found in equation (2), the notation vector has been expressed. Where b the displacement variable, Z denotes the notation vector, and δ_j the j^{th} slack variable. The mining of association rules between the data leads to a soft interval sample resolution of the vectors by the association rules between conditional attributes B and decision attribute A . First, a subset of conditional attributes is randomly chosen, B_1 Calculate the laws of the relationship of $B_1 \rightarrow A$; Iteration is then proceeded to adjust the subcomponent of the L^{th} time state B_1 Attribute below the minimum trust ϕ ; Finally, use the existing laws on income affiliation as mining results. Equation (2) expressed the notation interval to improve fault tolerance based on the soft interval mechanism.

The linear kernel dimension reduction technique is applied, which reduces the dimensionality of large space spaces while maintaining the initial low-dimension shape, improves processing speed, and reduces memory utilization. A high-dimensional i dimensional eigenvector C'_j for example, developments the data to a hyperplane and introduces the kernel feature in equation (3):

$$L(y_j, y_i) = \varphi(y_j)^S \varphi(y_i) \quad (3)$$

Equation (3) finds the kernel linear dimensionality for reduction, and a dimensional eigenvector has been performed. L it represents the time, (y_j, y_i) is signifies the hidden variables with time, ϕ is minimum confidence, S demonstrates the dimensional space, low-dimensional vector derives the following formula C'_j after dimensionality reduction in equation (4).

$$C'_j = C'_j \varphi(Y) \quad (4)$$

The above equation (4) to explore dimensionality reduction has been expressed. The estimation index S can be computed by the following equation (5):

$$S = Z^S U \quad (5)$$

As demonstrated in equation (5), an evaluation score has been founded to analyze the teacher teaching quality. Where S denotes the last estimation amount of a teacher's teaching ability, U the teacher's teaching ability index vector, and Z the weight vector.

Figure 3 elaborates on the hidden Markov model variables. The HMM is typically used for time series data modeling and is generally recognized in machine-length learning and adaptive Bayesian network with a specific framework for image detection, computer vision, and language processing. In the HMM, the complex, non-observable variables can be estimated and inferred based on observed variables. It is particularly suitable to measure student mastery of a series of information points in the student PE courses. Given the variation between student capabilities and the broad discrepancies between professional PE ventures, standard research approaches frequently struggle to assess real-time and high precision of the individual student's learning results. The machine learning HMM can only predict unknown variables using the probabilistic graphic model using observed known variables. The established variables observed are referred to as observation variables, and the unknown variables are considered latent variables. Figure 3 illustrates the degree of mastery of several knowledge points, and the vector of observation $\{x_1, x_2, \dots, x_m\}$ represents the results for several knowledge points. For example, the observer variable $\{y_1, y_2, \dots, y_m\}$ represents the results. Generally speaking, the hidden Markov model equations appropriate for student assessment can be broken down into four stages:

- i) The joint probability distribution of the HMM shown in Figure 3 can be defined in equation (6):

$$Q(x_1, y_1, \dots, y_m, x_m) = Q(x_1) Q\left(\frac{y_1}{x_1}\right) \prod_{j=2}^m Q\left(\frac{x_j}{x_{j-1}}\right) Q\left(\frac{y_j}{x_j}\right) \quad (6)$$

As explored in equation (6) joint probability function has been derived to find the college student learning effect. Q express the joint probability of the HMM.

- ii) The probability of state conversion mentions the state transition likelihood of the model between the two knowledge points earlier and afterward themselves. The probability of performance observation refers to the probabilities of each knowledge point in the present state. The probability of the initial condition mentions the probability of a test point in the original state. The three chances are shown in the formula in equation (7):

$$\begin{aligned} B_{ji} &= Q\left(X_2 = \frac{i}{X_1} = j\right) \\ A_{ji} &= Q\left(X_1 = \frac{i}{X_2} = j\right) \\ D_j &= Q(X_1 = j) \end{aligned} \quad (7)$$

Step 2 or equation (7) to find the state transition probability, and initial probability, output observation probability.

Figure 4 expresses the hidden Markov model. Figure 4 shows two facets of the teacher's and student's learning in the PE teaching assessment model suggested in the report. The former is done by data processing technologies to evaluate

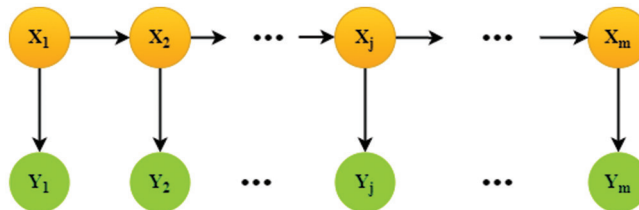


Figure 3: Hidden markov model (HMM) variables.

teachers. The above is finished with the assessment by the HMM. In the end, an aggregate assessment of the standard of education is achieved using the assessment of the teacher's capacity and the assessment of the learning impact of the students.

- iii) Choose the first initial state according to the initial likelihood D_j ; then pick, according to the initial condition and the probability of production observer A_{ji} the following vector condition dependent upon the initial state and the probability of state transformation B_{ji} .
- iv) If all points of experience are iterated, $\{y_1, y_2, \dots, y_m\}$ is the hidden variable position.

In addition, there are two parallel processing computations: One to assess the capacity of the instructor to read and the other to determine the educational impact on the students. Let us first add the measurement of the processing to evaluate teaching ability. The following two steps will separate this operation.

Collect actual information from a certain number of teachers as training data. For each indicator $J1 \sim J10$ shown in the table by training the corresponding weights $Z1 \sim Z2$;

Figure 5 performs the HMM-based knowledge point and tests. Calculate teachers' capacity to be assessed. Concerning the teachers' data to test, prepare the data, and then accumulate each indicator data in a weighted method. The findings are the products of the teacher's ability to assess. That is, the instructor's teaching ability will measure the score T_s using the following formula in equation (8)

$$T_s = \sum_{j=1}^{10} J_j \times Z_j \tag{8}$$

As calculated in equation (8) score value of the teacher teaching effect for student performance. Let's then add the processing calculation to assess the learning impact on the students.

The students to be tested will calculate their learning impact. The HMM approach tests the student's learning impact by the hidden variable measurement method. The T_l assessment ranking is as follows in equation (9):

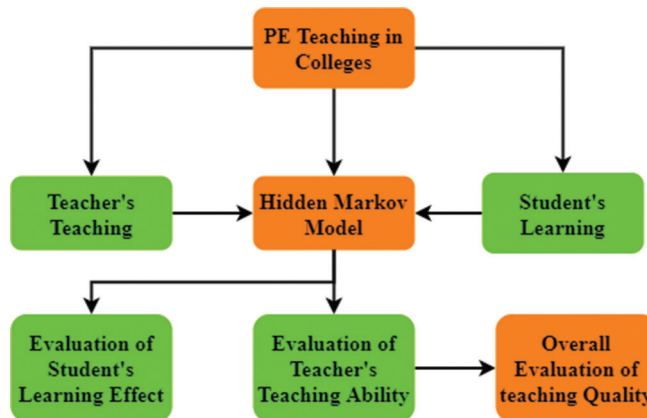


Figure 4: Hidden markov model.

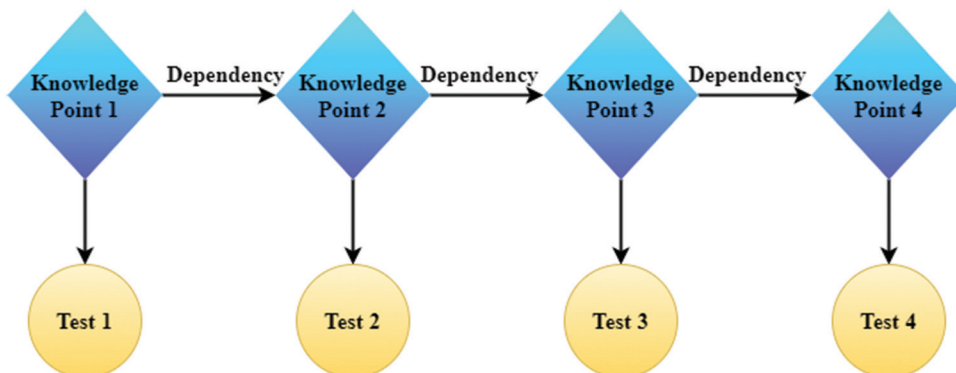


Figure 5: HMM-based knowledge point and tests.

$$T_t = \sum_{j=1}^m L_j \times U_j \quad (9)$$

As computed in equation (9), assessment ranking has been expressed. Where m represents the number of knowledge points and U_j the weight of the learning effect evaluation of the j^{th} knowledge point L_j the learning effect estimation score of the j^{th} knowledge point.

After evaluating the teacher's skills, T_s and student's learning impact, T_s , the overall PE assessment score can be obtained through the following formula in equation (10):

$$T = T_s \times 0.7 + T_t \times 0.3 \quad (10)$$

The overall evaluation has been described in equation (10). Where, T_s is 0.7 in weight, T_t is 0.3 in weight. In this research, students are the key teaching elements, and measuring the students' learning impacts is more important than evaluating teachers' teaching capabilities.

Figure 6 signifies the PA prediction. For the sports prediction problem, it is necessary to maintain the training data order such that matches are forecast based on past matches. In the case of one season with data on hand, it is necessary to decide the number of rounds used for model training and the number of rounds used for model checking. The first seven competitive rounds for the model's training could collect ten information rounds. The last three competitive rounds could be used for model testing.

However, round one could be used as training for testing in rounds two, 1, and 2 to assess model results; rounds 1 and 3 could be used as training for round 4. Then, we use rounds 1:1 to train and use round $n; n \in N$ as test data set in rounds 1:1 in each round of N , in which N is the total number of rounds in the game in a season that includes a certain number of competition rounds. This allows us to accurately classify another way to refresh the training data collection for each match would be to do a round-by-round simulation. Both previous PA as training specifics up to the present match and the next PA as training information is included in this situation. May be not necessary as teams compete in the same contest round something more than around.

4. Numerical Results and Discussion

This paper discussed machine learning-based physical training for college students to improve curriculum and enhance learning outcomes in PE. This paper aims to establish the relationship between sports participation and student university

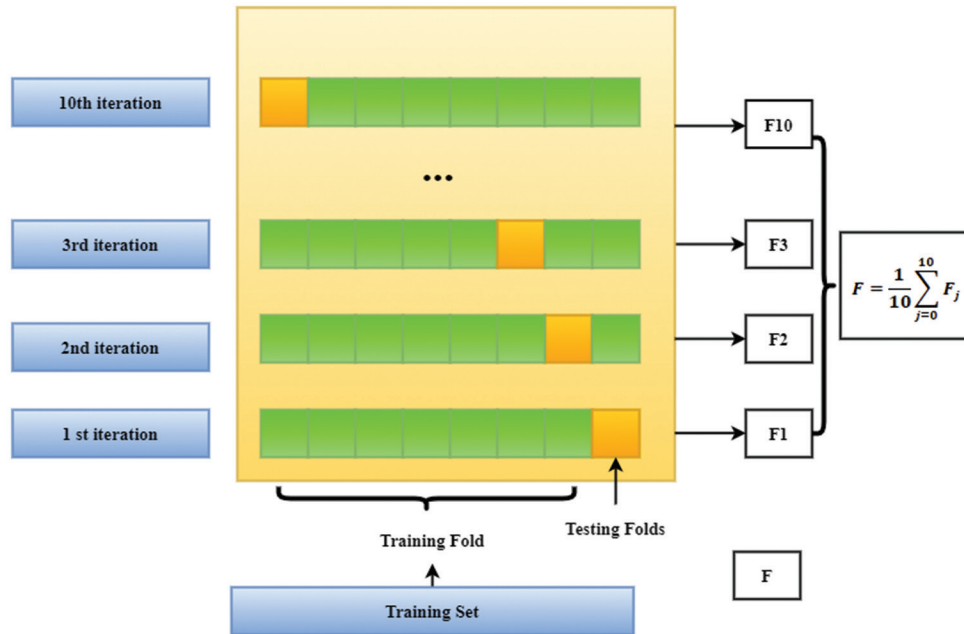


Figure 6: Physical activity prediction.

success. Based on this study, the students who regularly participate in sports have found their research successful. Both of these have meant that students tend to be more disciplined and more adventurous in offering classroom ideas. Hence, in this paper, ML-PTF has been proposed to monitor the student’s physical training and the increased physical health based on the student involvement in learning.

In comparison to the FPGA-based ADRT platform, MLPFEM PARM model, and VRS methods, this section (Section 4) provides an in-depth explanation of the PE outcome’s functionality using parameters such as recognition accuracy ratio, learning rate, participation ratio, precision ratio, student interaction ratio, probability ratio, and F1-score. The analysis of the proposed method’s performance involves the evaluation of these parameters with data from 100 students on the X-axis.

4.1. Recognition accuracy ratio

Accelerometric evaluations of physical exercise involve enhanced recognition methodologies utilizing machine-learning methods. These machine-learning algorithms aim to accurately predict the type and intensity of physical exercise for college students’ physical education (PE) outcomes. Pattern analysis techniques, such as those found in machine learning, provide an alternative approach to traditional cutoff processes.

Machine-based pattern recognition is an AI division that deals with the classification or description of findings to predict results based on prior information or recognizable characteristics in the raw data. Accelerometer data analysis techniques were demonstrated to provide exact PA estimates and more precise evaluations of PA strength. Figure 7 shows the recognition accuracy ratio (%). In this figure, the highest response accuracy rate of 94.11% was observed for the proposed model compared to the existing models at the student count taken as 100. The lowest was observed for the model VRS.

4.2. Student interaction level (%)

Sports events, including lower levels of depression symptoms and raising pleasure and satisfaction with life, have been linked to improving students’ fitness. Besides this, students can make more connections by engaging in athletics, extending their perspective, and providing educational opportunities and a sports career. They need to relieve themselves of exhausting academic work by taking part in machine-based sports. Thus, it cannot be ignored that the students will benefit a lot from such social events on campus.

Maybe the university’s commitment to sports training is low or underlined. All the potential reasons are related to the student’s participation in sports in one environment, which shows considerable knowledge gaps in student success. Figure 8 depicts the student interaction level. The proposed ML-PTF was given an improved interaction

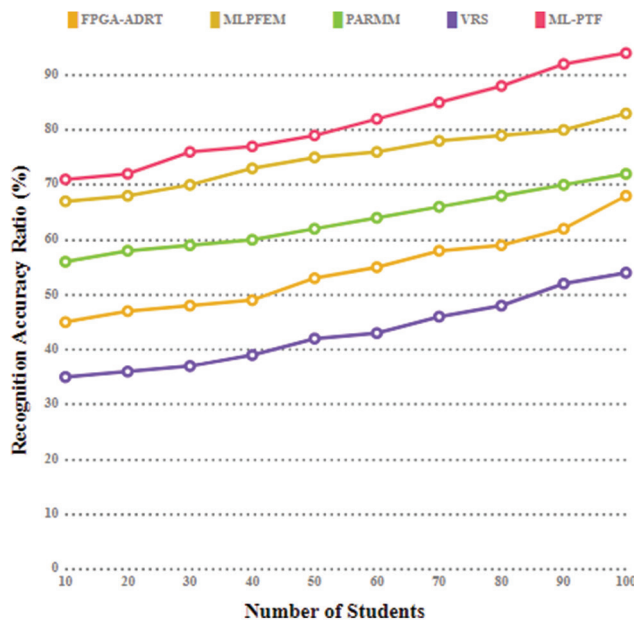


Figure 7: Recognition accuracy ratio (%).

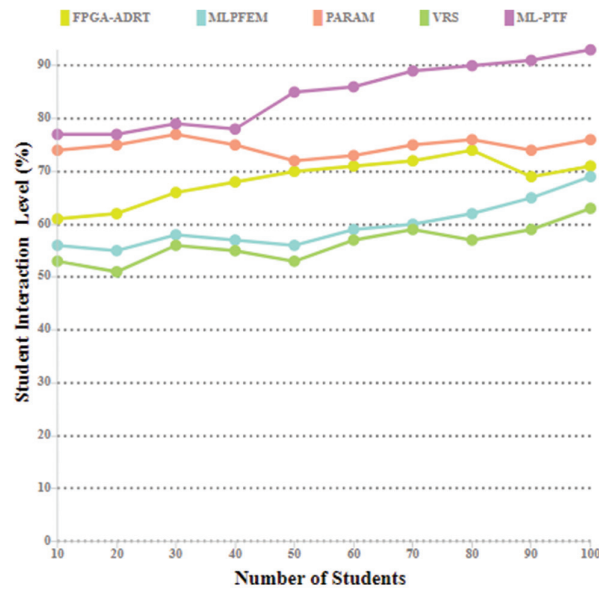


Figure 8: Student interaction level.

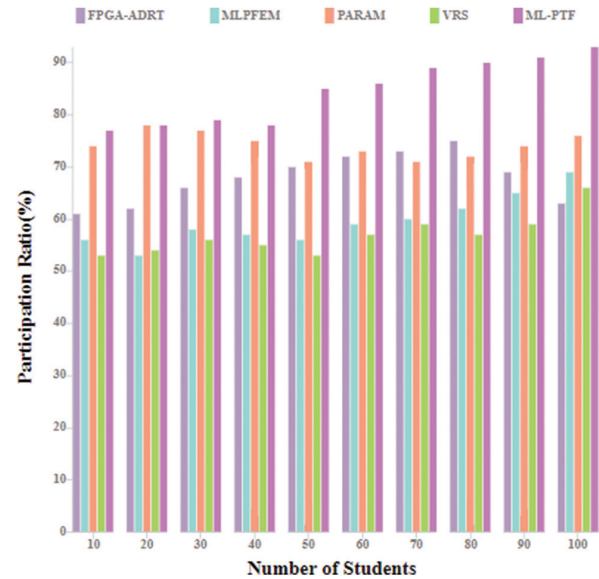


Figure 9: Participation ratio (%).

level when the number of students rises. The maximum rate was observed as 95.34% for ML-PTF compared to other models.

4.3. Participation ratio

The proposed ML-PTF is a personalized approach to teaching and learning that provides the teacher with input after processing data in real time. This allowed an instructor to understand student interest quickly, take corrective action, and improve student involvement and, thus, overall performance. Individual ideas and expectations of the students can be followed simply by real-time feedback using machine learning. This input can further develop the instruction, subjects, and technique.

Machine education makes the mechanism for the judgment process automated and analyses the student's individual data. The evaluation process was simplified, precise, and impartial with machine learning. Machine learning will be effective shortly and will yield much better outcomes. Figure 9 signifies the participation ratio. The above figure shows that when the number of students increases, the participant ratio rises to 92.16% for ML-PTF.

4.4. Precision ratio (%)

The proportion of the true positive (TP) and false negatives (FN) is precise; it is measured as accuracy. TP: The regular steps threshold had been exceeded and forecast; true negative: the regular measures threshold has not been exceeded and forecast; FN: the regular steps threshold has been exceeded, not predicted; false positive: The regular stage threshold has not been reached and has not been expected.

$$precision = \frac{TP}{TP + FN} \tag{11}$$

Equation 11 was used to compute the precision rate of the model prediction, which is commonly used to evaluate many ML-based models. The following figure shows the observed results with various students' sets for the proposed and other existing models.

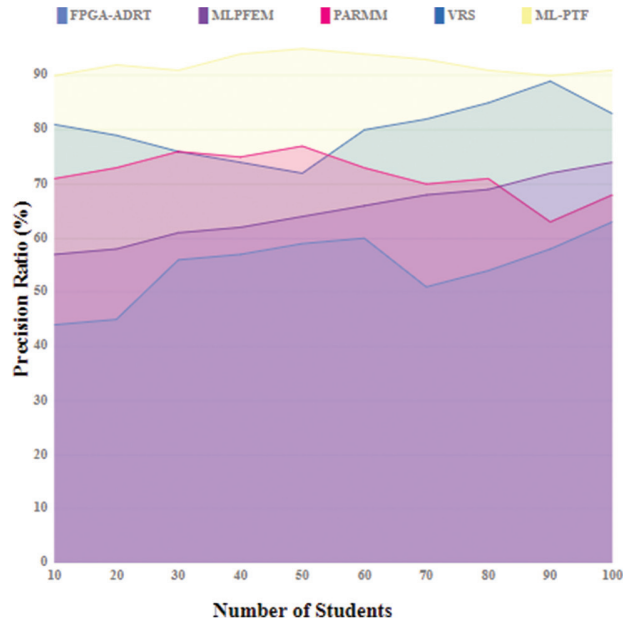


Figure 10: Precision ratio (%).

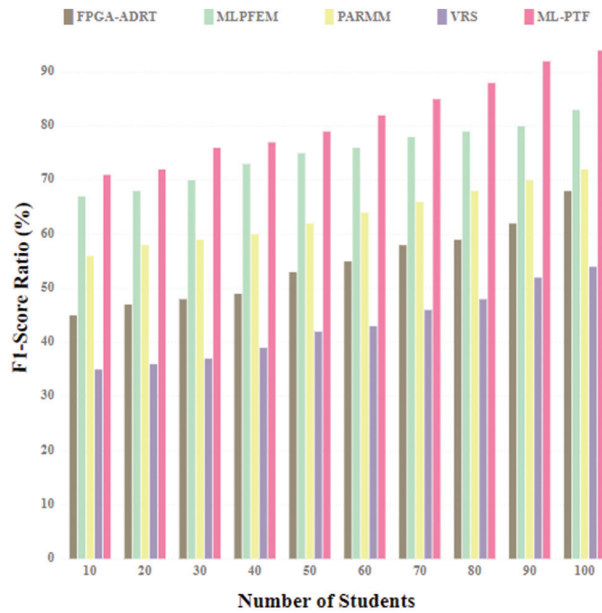


Figure 11: F1 Score ratio (%).

The highest precision ratio compared to the existing model, as shown in Figure 10, shows that the proposed model can perform well while implementing it in real time. This comparison chart can validate the excellence of the proposed model in the current scenario, overcoming existing models' challenges.

4.5. F1 score ratio (%)

The F1 score takes values between zero and one, which correlates with the best result, similar to the accuracy metric. The proposed ML-PTF uses two other metrics: Accuracy and a model reminder to measure the F1 score. The F1 score is calculated below equation (12):

$$F1\bar{score} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (12)$$

As found in equation (12), F1 score value has been determined. The F1 score is an indicator of the consistency of a model of a dataset. It is used for evaluating binary schemes of classification that label examples as positive or negative.

Table 1: Learning rate

Number of devices	FPGA-ADRT	MLPFEM	PARMM	VRS	ML-PTF
10	46.15	62.11	51.01	38.22	81.17
20	44.16	66.13	55.13	31.24	82.15
30	48.17	68.05	58.24	34.23	85.13
40	52.11	63.01	62.25	37.25	87.16
50	53.18	65.01	65.26	38.27	88.15
60	51.01	67.09	67.33	45.09	89.32
70	52.12	62.01	69.21	48.13	91.17
80	55.03	59.13	64.35	53.08	93.14
90	59.19	62.19	65.34	56.22	94.11
100	63.15	64.11	67.27	66.12	94.14

FPGA: Field programmable gate arrays, ADRT: Adaptive data reinforcement technique, MLPFEM: Machine learning-based physical fitness evaluation model, ML-PTF: Machine learning aided physical training framework

Table 2: Probability ratio (%)

Number of devices	FPGA-ADRT	MLPFEM	PARMM	VRS	ML-PTF
10	28.12	41.11	53.21	36.05	84.05
20	31.24	45.23	56.23	34.06	86.06
30	34.13	48.34	58.15	38.07	88.02
40	37.15	52.35	63.11	42.01	81.05
50	38.17	55.36	68.10	49.08	83.06
60	42.19	57.23	69.19	51.11	85.23
70	46.23	59.11	64.21	54.02	88.05
80	51.18	64.25	60.03	55.13	92.03
90	58.32	66.24	62.09	59.09	93.08
100	61.22	69.47	73.01	65.05	95.12

MLPFEM: Machine learning-based physical fitness evaluation model, VRS: Virtual reality system, ML-PTF: Machine learning aided physical training framework, FPGA: Field programmable gate arrays, ADRT: Adaptive data reinforcement technique

The F1 score evaluates knowledge recovery systems such as search engines and various machine learning models, particularly natural language processing. Figure 11 shows the F1 score ratio. The f1-score score for the proposed model is 93.14%, as seen in the above figure.

4.6. Learning rate

Modern use of technology in the expert method of PE makes ML useful in sports instruction and learning from abstract to real, leading to a better understanding and utilization of intelligent technology. Actual growth includes ensuring a healthier and more orderly development of functional sports knowledge. The teachings and learning environment have been regulated directly to protect students from various stimulus measures, keeping the nervous system excitable and facilitating successful teaching activity.

The use of teaching technologies has multiple benefits for ML. This study initially explains the conception and category of ML and then analyses in more depth the use in the modern vision and development of PE technologies and, at the same time, describes the problem of ML of modern applications in sports education technology. The study outlines ML's main strategy for modern sports education technology. Table 1 expresses the Learning rate.

4.7. Probability ratio

The employment of an activity tracker to oversee the daily count of participants engaging in physical education strategies aligns with gauging the success of participants in attaining their individual step objectives throughout the day. In the context of automatically tailored guidance, the incorporation of machine learning could present a vital edge. These personalized algorithms enable the anticipation of physical activity (PA) over the course of the day, facilitating timely responsiveness. The probability ratios (%) are outlined in Table 2.

The experimental results show that the ML-PTF has been proposed to reduce student disability in PE, enhance learning rate, high student interaction level, and increase participation, f1-score, precision, probability, and recognition accuracy when compared to other FPGA-based ADRT platform, MLPFEM, PA PARM model, and VRS methods.

5. Conclusion

This paper analyzed PE based on machine learning to improve curriculum and enhance PE outcomes. Physical training provides specifically the necessary skills to communicate with others. It enabled the development of leadership and collaboration skills and prepared students to translate their knowledge to other educational fields. Students dedicate themselves to physical fitness, and it has unaffected learning contexts. Students at universities could engage in athletic activity to see how it impacts the students themselves and others. Therefore this paper, ML-PTF, was proposed to analyze student performance and student attention in PE. This paper thus provided detailed research on the overall evaluation of the PE teaching effect in colleges from the viewpoint of the teaching skills to student learning effect and the HMM to improve further the teacher-level evaluation of the PE program. Thus, the experimental results were shown that the ML-PTF could improve student performance in PE learning, enhance learning rate 94.14%, high student interaction level 95.34%, increase participation 92.16%, f1-score 93.14%, precision 93.15%, probability 95.12%, and recognition accuracy 94.11% compared to existing methods.

6. Funding

“This research received no external funding”

7. Conflicts of Interest

“The authors declare no conflicts of interest.”

References

- [1] H. Shi, H. Zhao, Y. Liu, W. Gao, and S. C. Dou, “Systematic Analysis of a Military Wearable Device Based on a Multi-level Fusion Framework: Research Directions,” *Sensors (Basel)*, vol. 19, no. 12, p. 2651, Jun. 2019, doi: 10.3390/s19122651.
- [2] H. Agarwal, K. Somani, S. Sharma, P. Arora, P. S. Lamba, and G. Chaudhary, “Palmprint Recognition Using Fusion of Local Binary Pattern and Histogram of Oriented Gradients,” *Fusion: Practice and Applications*, vol. 1, no. 1, pp. 22-31, Jan. 2020.
- [3] E. W. Nettleton, and H. F. Durrant-Whyte, “Delayed and asequent data in decentralized sensing networks,” in: *Sensor Fusion and Decentralized Control in Robotic Systems IV*. Vol. 4571. SPIE, France, pp. 1-9, Oct. 2001.

- [4] Z. Y. Algamil, M. R. Abonazel, and A. F. Lukman, "Modified Jackknife Ridge Estimator for Beta Regression Model with Application to Chemical Data," *International Journal of Mathematics, Statistics, and Computer Science*, vol. 1, pp. 15-24, 2022. doi: 10.59543/ijmscs.v1i.7713.
- [5] N. Hameed, A. M. Shabut, M. K. Ghosh, and M. A. Hossain, "Multi-class Multi-level Classification Algorithm for Skin Lesions Classification Using Machine Learning Techniques," *Expert Systems with Applications*, vol. 141, p. 112961, Mar. 2020.
- [6] W. Huifeng, S. N. Kadry, and E. D. Raj, "Continuous Health Monitoring of Sportsperson Using IoT Devices Based Wearable Technology," *Computer Communications*, vol. 160, pp. 588-595, Jul. 2020.
- [7] S. Qiu, H. Zhao, N. Jiang, Z. Wang, L. Liu, Y. An, H. Zhao, X. Miao, R. Liu, and G. Fortino, "Multi-sensor Information Fusion Based on Machine Learning for Real Applications in Human Activity Recognition: State-of-the-art and Research Challenges," *Information Fusion*, vol. 80, pp. 241-265, Apr. 2022.
- [8] U. M. Khan, Z. Kabir, S. A. Hassan, and S. H. Ahmed, "A Deep Learning Framework using Passive WiFi Sensing for Respiration Monitoring," in: *GLOBECOM 2017-2017 IEEE Global Communications Conference*, IEEE, New Jersey, pp. 1-6, Dec. 2017.
- [9] J. L. A. Kumar, M. Sarkar, S. Mohanty, and S. H. Ahmed, "A Comparative Study of MAC Protocols in Brain-Computer Interface (BCI) Applications," in: *2017 13th International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, New Jersey, pp. 1522-1527, Jun. 2017.
- [10] V. Balasubramanian, and A. Jolfaei, "A Scalable Framework for Healthcare Monitoring Application using the Internet of Medical Things," *Software: Practice and Experience*, vol. 51, pp. 2457-2468. Dec. 2020.
- [11] R. Amin, S. H. Islam, G. P. Biswas, M. K. Khan, and N. Kumar, "A Robust and Anonymous Patient Monitoring System Using Wireless Medical Sensor Networks", *Future Generation Computer Systems*, vol. 80, pp. 483-495, Mar. 2018.
- [12] C. Verma, V. Stoffová, Z. Illés, S. Tanwar, and N. Kumar, "Machine Learning-Based Student's Native Place Identification For Real-Time," in *IEEE Access*, vol. 8, pp. 130840-130854, Jul. 2020.
- [13] J. Bobadilla, F. Ortega, A. Gutiérrez, and S. Alonso, "Classification-based Deep Neural Network Architecture for Collaborative Filtering Recommender Systems," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 1, pp. 68-77, Mar. 2020.
- [14] J. Bobadilla, A. Gutiérrez, S. Alonso, and R. Hurtado, "A Collaborative Filtering Probabilistic Approach for Recommendation to Large Homogeneous and Automatically Detected Groups," *International Journal of Interactive Multimedia and Artificial Intelligence*, vol. 6, no. 2, pp. 1-11, Jun. 2020.
- [15] M. S. Kumar, V. S., Dhulipala, and S. Baskar, "Fuzzy Unordered Rule Induction Algorithm Based Classification for Reliable Communication using Wearable Computing Devices in Healthcare," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, pp. 1-12, 2020, doi: 10.1007/s12652-020-02219-0.
- [16] A. B. Mesanza, S. Lucas, A. Zubizarreta, I. Cabanes, E. Portillo, and A. Rodriguez-Larrad, "A Machine Learning Approach to Perform Physical Activity Classification Using a Sensorized Crutch Tip," in *IEEE Access*, vol. 8, pp. 210023-210034, Nov. 2020.
- [17] J. M. Giménez-Egido, E. Ortega, I. Verdu-Conesa, A. Cejudo, and G. Torres-Luque, "Using Smart Sensors to Monitor Physical Activity and Technical-Tactical Actions in Junior Tennis Players," *International Journal of Environmental Research and Public Health*, vol. 17, no. 3, pp. 1068, Feb. 2020.
- [18] U. A. R. Chaudhry, C. Wahlich, R. Fortescue, D. G. Cook, R. Knightly, and T. Harris, "The Effects of Step-Count Monitoring Interventions on Physical Activity: Systematic Review and Meta-Analysis of Community-Based Randomised Controlled Trials in Adults," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 17, no. 1, p. 129, Oct. 2020, doi: 10.1186/s12966-020-01020-8.
- [19] A. Nadeem, A. Jalal, and K. Kim, "Accurate Physical Activity Recognition using Multidimensional Features and Markov Model for Smart Health Fitness," *Symmetry*, vol. 12, no. 11, p. 1766, Oct. 2020. doi: org/10.3390/sym12111766
- [20] J. Qi, P. Yang, L. Newcombe, X. Peng, Y. Yang, and Z. Zhao, "An Overview of Data Fusion Techniques for Internet of Things Enabled Physical Activity Recognition and Measure," *Information Fusion*, vol. 55, pp. 269-280, Sep. 2020.
- [21] S. Jeong, C. Choi, and D. Oh, "Development of a Machine-Learning based Human Activity Recognition System including Eastern-Asian Specific Activities," *Journal of Internet Computing and Services*, vol. 21, no. 4, pp. 127-135, Aug. 2020.
- [22] J. Stålesen, T. Westergren, B. H. Hansen, and S. Berntsen, "A Mapping Review of Physical Activity Recordings Derived From Smartphone Accelerometers," *Journal of Physical Activity and Health*, vol. 17, no. 11, pp. 1184-1192, Oct. 2020.
- [23] D. E. Conroy, C. M. Lagoa, E. Hekler, and D. E. Rivera, "Engineering Person-Specific Behavioral

- Interventions to Promote Physical Activity,” *Exercise and Sport Sciences Reviews*, vol. 48, no. 4, pp. 170-179, Oct. 2020, doi: 10.1249/JES.0000000000000232.
- [24] M. M. Jaber, M. H. Ali, S. K. Abd, M. M. Jassim, A. Alkhayyat, B. A. Alreda, A. R. Alkhuwaylidee, and S. Alyousif, “A Machine Learning-Based Semantic Pattern Matching Model for Remote Sensing Data Registration,” *Journal of the Indian Society of Remote Sensing*, vol. 50, pp.1-14, 2022.
- [25] H. Ma, W. Li, X. Zhang, S. Gao, and S. Lu, “AttnSense: Multi-level Attention Mechanism for Multimodal Human Activity Recognition,” in: *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, pp. 3109-3115, Aug. 2019.
- [26] K. Moorthy, M. H. Ali, M. A. Ismail, W. H. Chan, M. S. Mohamad, and S. Deris, “An Evaluation of Machine Learning Algorithms for Missing Values Imputation,” *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 12S2, pp. 415-420, 2019.
- [27] K. Tao, W. Liu, S. Xiong, L. Ken, N. Zeng, Q. Peng, and Z. Gao, “Associations Between Self-Determined Motivation, Accelerometer-Determined Physical Activity, and Quality of Life in Chinese College Students,” *International Journal of Environmental Research and Public Health*, vol. 16, no. 16, p. 2941, Aug. 2019, doi: 10.3390/ijerph16162941.
- [28] M. S. Kim, and B. J. Cardinal, “Differences in University Students’ Motivation between a Required and an Elective Physical Activity Education Policy,” *Journal of American College Health*, vol. 67, no. 3, pp. 207-214, 2019.
- [29] M. V. Solís, P. A. Sánchez-Miguel, M. A. T. Serrano, J. J. Pulido, and D. I. Iglesias, “Physical Activity as a Regulatory Variable between Adolescents’ Motivational Processes and Satisfaction with Life,” *International Journal of Environmental Research and Public Health*, vol. 16, no. 15, p. 2765, Aug. 2019, doi: 10.3390/ijerph16152765.
- [30] C. Pan, “Design of Sports Course Management System Based on Internet of Things and FPGA System,” *Microprocessors and Microsystems*, vol. 80, p. 103357, 2021.
- [31] J. Guo, L. Yang, R. Bie, J. Yu, Y. Gao, Y. Shen, and A. Kos, “An XGBoost-based Physical Fitness Evaluation Model using Advanced Feature Selection and Bayesian Hyper-Parameter Optimization for Wearable Running Monitoring,” *Computer Networks*, vol. 151, pp. 166-180, Mar. 2019.
- [32] C. L. Zhong, “Internet of Things Sensors Assisted Physical Activity Recognition and Health Monitoring of College Students,” *Measurement*, vol. 159, p. 107774, Jul. 2020.
- [33] Y. Ding, Y. Li, and L. Cheng, “Application of Internet of Things and Virtual Reality Technology in College Physical Education,” in *IEEE Access*, vol. 8, pp. 96065-96074, May. 2020.