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5G NETWORK TECHNOLOGY-BASED REFINEMENT AND DEVELOPMENT IN PHYSICAL EDUCATION PERFORMANCE

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Abstract—Generally, physical education (PE) is one of the fundamental ability developments of human healthiness. In society, there are many challenges to enlarge the performance in Chinese physical activities. Also, the involvement of 5G communication network technology becomes an advent in physical activity expansion day-by-day in China. Physical activity can help to improve the Chinese's mental ability, self-concept, aim orientation and also prevent states like depression, anxiety, etc. Physical activity without education is like having a body without a soul. There is no debate about the importance of physical education and various forms of exercise in the overall educational system. The PE teaching performance of Chinese developed by several network technologies such as artificial neural networks, IoT, machine learning, This paper approaches the development and refinement in physical education teaching based on 5G network technology to obtain everlasting data without termination. Firstly the sports dataset can be pre-processed using a stacked denoising autoencoder (SDAE). Gaussian Mixture Model (GMM) is utilized for the feature extraction process. A random forest approach (RFA) can be used in the selection of the features. The classification is done by using a CNN-based upgraded classifier. An efficient data allocation (EDA) algorithm is used for storing data in a 5G network. The stored data can be enhanced by using the glowworm swarm optimization (GSO) technique. The result can be simulated in the MATLAB software tool. Finally, the performances such as accuracy, sensitivity, specificity, and memory utilization of various classifiers are analyzed in this paper.

Keywords: **Physical education (PE), stacked denoising autoencoder (SDAE), Gaussian Mixture Model (GMM), Random forest approach (RFA), CNN based upgraded classifier, and an Efficient data allocation (EDA) algorithm**

I. INTRODUCTION

Higher education reform has become more in-depth, the expansion of education in universities and the strengthening of reform take place in this modern era. Since physical activity is an important aspect of the education process, its teaching effect is related to the future growth of national health and education. The current study reveals that students' primary fitness education has several issues, including a standard teaching approach, an absence of a distance teaching method, and an inability of extensive technical evaluation. The increasing need for physical education content among college students is always expanding with society's general growth. [1]

The physical education teaching objective is to improve students' skills in health and exercise; as a result, proper exercise routines and techniques are critical. The experts have identified a flaw in the regular way of teaching Physical Education and the individual’s emotional and physical characteristics are frequently overlooked.[2]

Global research has focused on networked physical education, particularly in the domains of digital learning. Its major purpose is to increase educational quality by utilizing established network devices and network communication modes. Interconnected primary fitness education, in particular, has made a huge impact during the COVID-19 period, as it has the potential to rapidly improve and expand teaching efficiency. However, networked physical activities are more widely recognized than conventional physical education. As a result, it's essential to build digital physical education by enabling interconnected physical education to have adaptive characteristics and improve latency and experience quality.[3]

The approach of physical education is influenced by a variety of aspects. The AI and machine vision can be implemented to support and construct physical education tasks, which increase the effectiveness of physical education, and gives a comprehensive teaching assessment method for the physical education system. [4]

Implementing computer-assisted instruction (CAI) in the area of physical training is a critical step in moving away from the usual framework towards the research and information, and it is one of the most difficult in the field. Artificial Information technology plays a vital role in computer-assisted training, and the integration of CAI and AI will enhance the teaching methods in such a manner that people can easily distinguish the module's teaching material, teaching topic, and teaching approach. The method and composition of physical education are based on information input from the student's learning theory, can be

easily differentiated within that way, achieving the AI system contents and logic, and typically influence physical teaching material and educational methods that lead to individual distinctions. [5]

The further part of this article is structured as shown. Section II offers the literary works associated with this paper. Section III explains the proposed model. Section IV provides the performance analysis of the suggested method. And, finally, section V concludes the overall idea of the paper.

II. Related Works

Lei et al., (2021) [6] proposed District standards for smartphones, such as the less information rate gadgets, consumption of power, and gadget of things, similar to Long Term Evolution (LTE). There is various developing Internet of Things standards that could help overcome this challenge. Its purpose is a major aspect in the future networking potential of the fifth-generation cellular network, which will replace the earlier smartphone's regular limit. Physical fitness benefits both students and the community as a whole. The first step is to improve overall physical condition. Physical education can help learners enhance and grow social skills such as flexibility, response time, speed, collaboration, balance, and basic body movement.

Zhan., (2020) [7] investigated and provided a detailed analysis of IoT and health care and physical activity solutions. . Existing research should be sorted and provided in the structure of fifth Generation medicine. In some circumstances, healthcare and physical activity are also essential for the success fifth generation integration. Finally, several important topics will be discussed about the constraints of investigating the Internet of things and fifth-generation healthcare and physical activity.

Cheng., (2021) [8] suggested that the data from the decision-making process of a device can be compared to the off-the-shelf standard to produce an evaluation and collective physical education process. The use of Genetic Algorithms in augmented reality for education and training support. The Virtual Reality (VR) development in this subject is constructed based on actual education and preparation. The VR innovative features and unique traits could be widely applied in actual training, with preparation playing a key role. The embedded system is a crucial component of today's electrical parts. Embedded equipment can normally run as a single program and can communicate with other network devices through a network connection. Users get some experience in a digital environment as a result of the equipment requirements. It is a significant step in the development of VR.

Li., (2021) [9] Analyzed the method of digital network classroom as a university physical fitness learning model. The development of research at the University of Physical Fitness Teaching Method in the digital classroom network can significantly guide and improve the student's learning interests and motivate them. More educators are recognized and engage in physical activity in digital classroom networks, which will benefit university education. The features of the fifth-generation digital network generation should be incorporated into the development of a university physical activity assessment process. Data gathering, data analysis, result production, and result feedback are all part of the evaluation process. The assessment methods provided fundamentally show the many parts of the physical activity system in universities, related to the knowledge of the fifth-generation digital network. In comparison to the existing approach, the exploration-based college physical education evaluation method has a degree of objectivity. As a result, it is possible to use a fifth-generation digital network to assess college physical education.

Zhu., (2021) [10] Investigated the changes in people's daily exercise routine and body composition of the previous and initial reform of education, we presented a combination of reforms at education and the experiment of digital integration with fifth-generation cloud computing communication technology. The following procedures were used: literature review, questions, teaching experiment, measurement, and quantitative statistics. The outcomes of digital fusion and combined education reform experiment with fifth-generation cloud computing communication technology represent that the education transformation can raise the university people who enrolled in sports while also influencing change in their body composition. As a result, a digital teaching method based on fifth-generation cloud computing communication technology is unavoidable in the reform of physical education programs. It can help students not only to develop physical fitness but also improve their health to some level. As a result, it supports China's excellent health strategy.

Chen et al., (2020)[11] proposed the transformation of the martial arts education system using the latest 5th generation technology. It has been realized the field Programmable Gate Arrayssystem integration in martial arts, based on the fifth generation and Field Programmable Gate Array integrated information service. The system was tested in an experimental setting. The "Sports and Health Curriculum Standards," which meets the teaching aim of the system's comprehensive transformation of martial arts education and serves as a reference for new physical and educational transformation programs.

Sun et al., (2021) [12] proposed the method for the creation of a new digital teaching way for physical education. To begin with, edge computing technology for the physical education system can significantly enhance the management system efficiency. Second, the Backpropagation neural network method altered by particle swarm is utilized to perform a depth interpretation of data of the college physical education management methods and get related optimization methods, which are based on data cleaning. Finally, experimental procedures show that the methods can execute alteration, removal, the search of data, entry, and other operations quickly, assuring that the university sports department can manage physical education resources in a digitalized manner.

Du et al.,(2021) [13] suggested that the Artificial Neural Network (ANN) system uses accelerometer measurements as its framework. Finally, a detailed view of technologies with suggested commercial products based on the FPGA tool is used to compare this study to the current development status. Technological advancements have opened new opportunities for improving instruction and the providing of the received PE gaming abilities. Motion tracking systems can give the proper abilities to develop skills in athletic teaching by estimating the location availability of people.

Xu et al., (2021) [14] investigated to assist the development of PE, using 6CNRD, a unique framework related to IPv6 Content Networking (6CN). 6CNRD is divided into two stages: the content delivery stage, which is identity forwarding, and the content request stage related to segment routing. Over a designed physical education topology, we compare 6CNRD to 2 cutting-edge methods, and the experimental findings reveal that 6CNRD has fewer delivery delays and routing. It also shows that 6CNRD has a broad range of applications not only to physical education.

Wang et al., (2019) [15] proposed a methodology for a group-centric physical education support mechanism that is related to cloud platforms and wristbands. These processes are classified into 3 parts related to event streams: Internet of Things node networking and configuration before class, real-time health monitoring and immediate urgent situation identification in class, and students' progress and course standard assessment after class, which gives physical teachers a comprehensive picture of their student’s fitness and exercise condition. Furthermore, a method is developed for educational purposes and to demonstrate the practicality of the suggested technique, as well as a comparison of our suggested methods with other methods.

Chao et al., (2021) [16] researched physical training teaching gadgets on cloud computing and big data. To gain complete knowledge of the study subject, this article mostly employs the questionnaire survey technique, data analysis techniques, experimental research methodology, and data statistics techniques. Experiments have proven that combining Big Data and Cloud Computing can successfully overcome the challenges that exist in the traditional teaching approach, allowing for efficient and speedy development.

Kaiyan et al.,(2018) [17] analyzed the number of people participating in physical activity has exploded in China as a result of the national fitness campaign's promotion. The lack of public sports venues has been identified as a barrier to the development of sports. This research provides an enhanced parallel heuristic map reduction technique and emphasizes constructing a network platform of all university sports venues resources that may achieve the aim of serving national fitness. The experimental results demonstrate the network platform of college sports venues' resilience, concurrency, and feasibility in the big data era.

Yu et al., (2021) [18] demonstrated that People's activity practices have shifted in the age of big data. University education will be subjected to significant changes because of the emergence of the big data era. In the coaching techniques, topics, and methodologies, big data can be utilized to enhance the ideas, materials, and methodologies to motivate students to study sports more richly and colorfully. As a result, the focus of this paper will be on university physical education reform in the big data era.

Dong ., (2021) [19] examined a college physical coaching information system based on big data mobile terminals, analyzed the big data embedded system, enhance the efficiency of training physical skills, and meet the need for highly trained athletes. This study investigates the advantages of big data using the survey method, detailed experimental techniques, and big data spectral clustering algorithm-related studies, as well as the value of big data and embedded system method, to examine the college physical activity coaching information system regarding the big data mobile terminal.

Sun.,(2020) [20] analyzed from the views of improved trends and innovation, this study focuses on the modifications of university sports based on AI and IOT technology to university Physical education management. The term "smart sports" was used to describe a concept that aims to address the demands of both people and sports. It is a novel idea, for future sports growth in China, as well as a major driving force in the creation of a sports power.

III. PROPOSED WORK

China released a study about implementing 5G technology in physical Education, indicating the commencement of the fifth generation-enabled physical education era. The objective of 5G-enabled physical teaching is to promote "Physical education" and how to successfully support the development of teenagers' physical activity habits. This section explains the flow of the suggested method. Figure 1 shows the schematic representation of the suggested methodology.

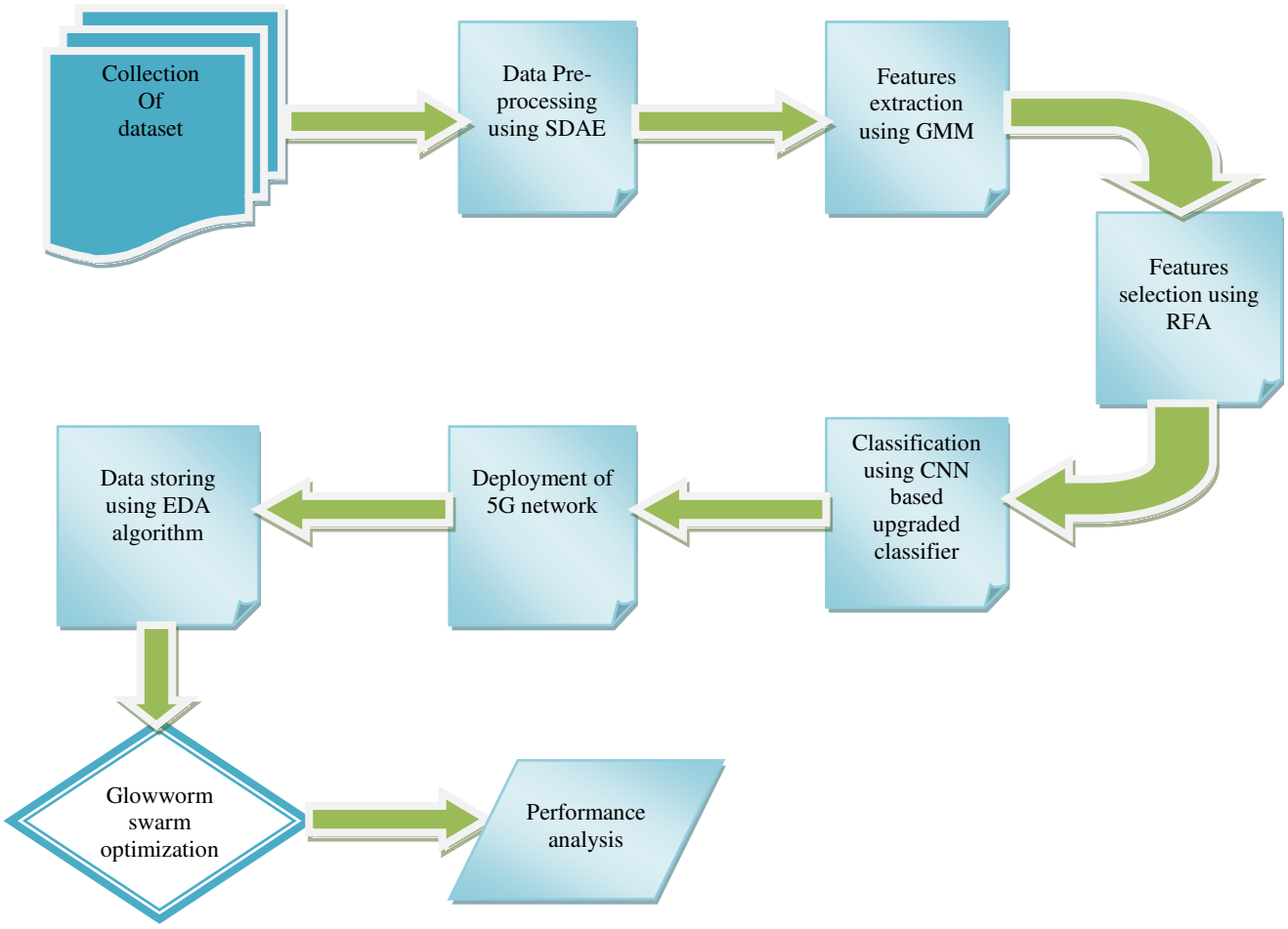


Figure 1: Schematic representation of the proposed method

A. Collection of dataset:

The PAMAP2 dataset was obtained from 10 people (7 men, 3 women) who were involved in 18 different physical activities. The participants were between the ages of 27 and 31 years, with a Body Mass Index of 25.11 to 2.62kg. Except for one who was sinistral, all of the participants were right-handed. Three IMUs and a heart rate monitor were used as sensor units to collect data. Three IMUs (Inertial Measurement Units) were put on the body in three locations: the hand, chest, and ankle. Each IMU has a three-axis gyroscope, a three-axis magnetometer, and two three-axis accelerometers, with the same sampling frequency. [21]

B. Data Pre-processing using Stacked Denoising Autoencoder:

The input and hidden layers of numerous denoising autoencoders are stacked in the stacked denoising autoencoder (DAE). DAE consists of three layers: hidden layer, input, and an output layer that uses encoders and decoders to obtain the output. To learn hidden features, the encoder can encode input data. The decoder can then decode the encoder's output and reorganize the data. Its purpose is to keep input and output as stable as possible while minimizing the loss between them. In addition, to prevent the problem of output being a straight copy of raw input, a denoising factor is utilized to corrupt input**.** The stacking denoising autoencoder training method is subdivided into two parts:

(i) pretraining

(ii) fine-tuning.

Pretraining :

The stacked denoising autoencoder uses layer-wise learning to upgrade specification in this stage. In a stacked denoising autoencoder, each denoising autoencoder is trained independently. Furthermore, until the entire network is trained, each DAE output will operate as an input to a future denoising autoencoder. Encoding and decoding are the two steps involved in the training of a denoising autoencoder. Our training data will be translated to a hidden layer in the encoding process using a sigmoid function, which is utilized to compress data, and it will be decoded using a sigmoid function.

Formally, let c_i denotes the input data, which have been previously classified and segmented.

c_i Is a 1*M vector. In this paper, the M equals 3071. The whole dataset is denoted, as follows:

$$P_a = \{c_0, c_1, \dots, c_a\} \tag{1}$$

Firstly, each c_i' is corrupted by a denoising factor a, which obtainc_i'. The possibility of every node lost in the layer is a. The encoding section,c_i' is mapped to the hidden layer by a sigmoid function s, namely

$$d = h(V_1 c_i' + b_1) \quad (2)$$

Where $V_1$and b_1 denotes the bias and weight matrix. Afterward, the x is mapped to the output Layer by a sigmoid function f, namely

$$z = g(V_2 x + b_2) \quad (3)$$

Where V_2 and b_2 denote the bias and weight matrix respectively. The inaccuracy between the generated data and the raw data is then estimated. The cross-entropy loss function is used, which is expressed as:

$$(c_i, z) = -\sum_{i=0}^{a}(c_i \log(z) + (1 - c_i \log(1 - z)) \quad (4)$$

Finally, gradient descent is used to update the parameters of each layer. The pretraining procedure is then completed.

Fine-Tuning:

A softmax layer is combined to the beginning of the network in this step, which is utilized to find the present activity type. After that, the entire network would be learned in a supervised way using labeled data, much like a Multilayer Perceptron (MLP). The criteria of the pretraining process are associated with the fine-tuning process, it should be mentioned. After then, backpropagation and gradient descent is utilized to fine-tune the parameters of each layer. During the training process, the entire dataset is proportionally partitioned into training, validation, and test sets.

C. Feature Extraction Using Gaussian Mixture Model:

Since a Gaussian Mixture Model can cope with a multimodal backdrop, it is commonly utilized in the search for physical movements. It estimates each pixel value using the mean and variance of all the sample pixels. Each pixel of the Gaussian Mixture Model is generated and updated with each new frame. At each new frame, some of the Gaussian matches the current value, and the running average updates the mean and variance for them.

Gaussian Mixture Model Updation :

GMM has three parameters that will update the pixels and frames one by one. Mean, Co-Variance, and Mixing Parameter are the parameters.

Mathematical Proof of the Gaussian Mixture Model:

The mathematical proof of the GMM is described in this section. GMM has three main parameters: covariance, mean, and mixing parameter. We demonstrate how to update these three parameters appropriately in these demonstrations.

Learning Gaussian Mixture Models:

The GMM$G(v) = \left(c_i(v)\right)_{i=1^m}$is a finite collection of m-sized clusters, each of which is given at the tth instant.

$$A_i(\mathrm{v}) = (\mu_i(v), \delta_i(v), \pi(v)) \tag{5}$$

Where,$\mu_i(v), \delta_i(v), \pi(v)$ are the covariance matrix, mean vector, and the mixing specification of $A_i(\mathrm{v})$ at the tth instant.

Initialization:

The GMM is initiated with a Single Cluster

$C_1(1) = (X_1; \delta_{init}; 1{:}\,0)$Where $X_1 is$ the data vector att=1 and δ_{init} is the initial covariance matrix whose values are selected from the domain knowledge.

Update:

In this sub-section, we deduce the equations for updating the GMM $G(v-1)$ learned to till the $(v-1)\ th$ to $G(v)$ with the present data vector X_V. We consider the data vector to be part of the cluster $c_j(v-1)$.

$$\left(X_V - \mu_j(v-1)^T \delta_J(V-1)^{-1}\left(X_v - \mu_j(v-1)\right)\right), n\lambda W \tag{6}$$

Here, λ is a user-defined threshold and n is the dimension of the data vector $X \in R^n$. In the first case, we assume that $\exists_j{:}\, X_v \in C_j(v-1)$. Let $S_i(\mathrm{v})$ be the number of data

Vectors that have been assigned to $C_i(\mathrm{v})$till the tth instant. Thus, we have

$$\pi_i(v) = \frac{S_i(v)}{v} \tag{7}$$

$$\pi_i(v) = \frac{(v-1)\pi_i(v-1)+\delta(i-j)}{v} \tag{8}$$

$$\pi_i(v) = (1-\alpha_i)\pi_i(v-1) + \alpha_i\delta(i-j) \tag{9}$$

Where $\alpha_v = \frac{1}{v}$

$\delta(i-j)$ is Kronecker's delta.

Now, we update the mean and co-variance in $C_j(v-1)$ only. To update the mean, we proceed as follows

$$\mu_i(v) = \frac{1}{S_i(v)}\sum_{X\in Aj(v)} X \tag{10}$$

$$\mu_i(v) = \frac{s_j(v-1)\mu_j(v-1)+X_v}{v\pi_j(v)} \tag{11}$$

$$\mu_i(v) = (1-\beta_j(v)\mu_i(v-1) + \beta_j(v)X_v \tag{12}$$

Where,$\beta_j(v) = \frac{\alpha_v}{\pi_i(v)}$

Similarly, we can update the covariance matrix. From the definition, we can compute the covariance matrix at the tth instant as,

$$\delta_j^2(v)$$

$$= \frac{1}{S_j(v)}\sum_{X\in A_{J(V)}} (X-\mu_j(v))\left(X-\mu_j(v)\right)(X-\mu_j(v))^T \tag{13}$$

$$\delta_j^2(v) = \frac{1}{S_j(v)}\sum_{X\in A_{J(V)}}(XX^T - \mu_j(v)\mu_j(v)^T) \tag{14}$$

Now, further manipulating, by substituting the update rule for$\mu_j(v)$, it can be shown that the updated co-variance matrix is given by,

$$\delta_j^2(v) = (1-\beta_j(v))$$

$$\begin{pmatrix} \delta_j^2(v-1)+ \\ \beta_j(v)(\left(X_j-\mu_j(v-1)\right)\left(X_i-\mu_j(v-1)\right)^T) \end{pmatrix} \quad (15)$$

In the second case, it may happen that$\exists_j: X_v \in C_j(v-1)$. In such cases, we initialize a new cluster $C_k(v) = (X_v; \delta^2{}_{init}; \alpha_v)$. If $G(v-1)$ has less than m clusters, then we add $C_K(v)$to it. Otherwise, $C_K(v)$ changes the cluster with the least weight. In these cases, the mixed specifications of all other clusters are penalized $\pi_i(v) = (1-\alpha_i)\pi_i(v-1); i \neq k$

D. Features selection using Random Forrest Approach:

The Random Forest (RF) algorithm was proposed by Leo Breiman and Adele Cutler as an integrated learning approach, which means it is made up of many small sub-models, with the output of each sub-model integrated to produce the final output. The RF algorithm is a typical machine learning algorithm that is utilized for regression, classification, and other learning tasks. To aggregate data from the original dataset, the RF algorithm uses a bagging technique. The decision tree model is established after each group has been trained. Finally, all of the sub-small model's decision data is integrated and processed to produce the final RF model**.** The RF technique can efficiently minimize the error of a single classifier and enhance the accuracy of classification by employing many classifiers for voting classification. Practical experience indicates that the RF algorithm has superior robustness and stability than artificial neural networks, regression trees, Support Vector Machine, and other algorithms and that the associated classification accuracy is leading level. The Random Forrest method is suitable for the huge processing of data and can adjust with high-dimensional data. It can retain high classification in the absence of data. The Random Forrest algorithm exceeds other classification algorithms in terms of categorization efficiency. It can handle enormous amounts of data, support huge varying parameters, and assess the value of varying attributes intuitively. Even many algorithms and practices have demonstrated that the Random Forrest algorithm has a better performance of classification and is more robust, stable, and efficient.

E. Classification using CNN based upgraded classifier:

To analyze physical teaching, this article employs a deep learning-based technology known as CNN. CNN, which is comprised of pooling, convolutional, and full connection layers, is the best domain in DL applications. Furthermore, several layers, such as the activation function layer, can considerably

minimize network time of training, improving the network ability and avoiding the dropout layer from overfitting. CNN is a hierarchical model in which the convolutional layer extracts the original data initially**.** The pooling layer accepts the dimension reduction data as the input of the lower convolution, which then repeats the pooling and convolution process. From the high-level information, the source data is sent. The required specification is upgraded by estimating the difference between the absolute and anticipated values, which is then integrated with the backpropagation technique to generate a convergence method. The convolution layer is at the heart of building a convolutional neural network in physical education. It is utilized to extract local image attributes after smoothing the input signal with the convolution kernel and filter. Because the depth of every convolution kernel fits the input data, the convolution kernel smoothes the breadth and height of the feature map to establish a new feature map. The first several layers' eigenvalues mostly belong to low-order attributes like horizontal and vertical edges. The last layers combine low-order attributes to form high-level aspects. These high-level characteristics are capable of distinguishing these data and mapping them to the space for categorization. The mapped physical teaching behavior data matrix is.

$$\begin{bmatrix} M_{11} & M_{12} & . & . & M_{1n} \\ M_{21} & M_{22} & . & . & M_{2n} \\ . & . & . & M_{ij} & . \\ . & . & . & . & . \\ M_{m1} & B_{m2} & . & . & M_{mn} \end{bmatrix} \tag{16}$$

The processing specification of the pooling layer is calculated using the data matrix acquired from the convolution layer. There is no specification to learn as compared to the convolution layer; instead, choose the greatest or average value from the targeted area, and then form these highest or mean values into a new feature map. Pooling is a downsampling procedure that decreases the number of specifications to minimize the network computational complexity. It can help prevent overfitting issues to some extent. Pooling is a way to minimize the spatial operation of a target area while maintaining the same number of input and output data channels. Furthermore, even if the data changes, pooling will produce the result, enhancing the network's stability. At this time, the result of the recognition is

$$B_i^{n+1} = \frac{1}{q}\sum[r-q]\frac{c}{z} \tag{17}$$

Input the identified result data to the CNN last layer, the whole connection layer, which merges every one of the previous layer's image attributes and typically transforms the 2D images produced by convolution into a 1D vector. Because the full connection layer does not retain image location data, it is difficult to maintain geometric features and then dimension modify from highest to lowest dimension while retaining valuable information. The feature vector is used as the classifier's input by the full connection layer of the CNN to acquire the relevant category's output and identify the original data. The objective function now enhances the output of physical teaching and the aim is to obtain

$$D(z) = \frac{1}{1+e^{v}} \tag{18}$$

The final identification results are denoted by D (z), while the corrected error value is denoted by e in the formula. In physical teaching, we use a CNN, connection layer, and pooling layer to assess the conduct using the objective function.

F. Deployment of 5G network:

The teaching method in the 5G network can be constructed using educational theory, merged with an exploration of the usual framework of the education method and the aspects of the 5G network, and under the design concepts of teaching physical education. It takes place in a 5G network classroom setting. Students actively seek the need and understand the essential elements of knowledge, and use self-inquiry as the mainstream of the education teaching methods under the guidance of teachers**.** We made effective utilization of the 5G network and the incorporation of the curriculum under the supervision of the teacher, granting students to recognize, analyze, and look online to find design and knowledge through the 5G networks classroom tools.

G. Data storing using efficient data allocation (EDA) algorithm:

When physical teaching resources are stable, the queuing model is utilized to determine the number of copies m backlog**.**

$$Q_{SRm=}\lambda_{SRm}R_{SRm=}\sum_{j=1}^{N}\lambda_i p_{im}\left(R_{wait}+R_{service}\right) \tag{19}$$

The steady-state copy m is obtained based on the utilization ratio of physical teaching,and the number of requests for physical teaching data resources is:

$$S_{SRm} = \frac{Q_{SRm}}{\rho_{SRm}} = \frac{\sum_{j=1}^{N} \lambda_i P_{im}(R_{wait}+R_{service})}{\rho_{SRm}} \tag{20}$$

Another optimization goal of the model is to obtain the task of physical teaching resources processing in the entire 5G network platform:

$$s_{total} = \frac{s_{total}}{\rho_{SRm}|S_{SR}|} = \frac{\sum_{j=1}^{M} \sum_{m=1}^{|S_{SR}|} \frac{\lambda_i P_{im} T_{SRm}}{\rho_{SRm}}}{|S_{SR}|} \tag{21}$$

The physical education resource scheduling problem for 5G networks is abstracted as a multi-objective optimization model in the synthesis: Determine the best allocation probability p_im. The average task volume is maximized as Stotal, according to the elasticity of physical teaching data resource allocation service, and the control function of resource allocation is obtained:

$$MinR_{total} = \sum_{j=1}^{N} (\lambda_i . \frac{\sum_{m=1}^{|S_{SR}|} P_{im} R_{SRm}}{\sum_{m=1}^{|S_{SR}|} \lambda_{SRm}} \tag{22}$$

$$MaxS_{total} = \frac{\sum_{j=1}^{N} \sum_{m=1}^{|S_{SR}|} \frac{\lambda_i P_{im} T_{SRm}}{\rho_{SRm}}}{|S_{SR}|} \tag{23}$$

The major requirement of the optimization technique is that the sum of the allocation probabilities must equal 1. The allocation of physical teaching resources is optimized based on the allocation.

H. Glowworm swarm optimization:

Glowworm Swarm Optimization (GSO) is a method for computing several multimodal function optima at the same time. The algorithm describes the computation that is carried out by aggregating swarms at optima in a more efficient manner. In GSO, each glowworm has its luciferin, which is a luminous compound. A glowworm with a greater luciferin value is in a better position in the search area and has a better attraction to its adjacent glowworm. The position of the glowworm will modify after each repetition, as will the luciferin value updated**.** The procedure of GSO methods are as follows:

Luciferin-update phase:

$$mu_i(v) = (1-\varphi)m_i(v-1) + \eta Q(w_{i(v)}) \tag{24}$$

Where $mu_i(v)$ denotes the updated luciferin value linked with glowworm i at time t, φ is the luciferin decay constant($0 < \varphi < 1$),η is the luciferin enhanced constant and $Q(w_{i(v)})$ is represented as the objective function of glowworm i at time v.

Movement phase:

$$Sr_{ij}(v) = \frac{f_k(v) - f_k(v)}{\sum_{k \in N_j(v)}(f_k(v) - f_i(v))} \tag{25}$$

here $Sr_{ij}(v)$ denotes the probability of movement for a glowworm motion to its neighbor node j at time v

Where $j \in N_i(v), N_I(V) = \{j; d_{ij}(v) < {r_d}^i(v); f_i(v) < f_j(v)\}$ (26)

Here $j$is the set of neighbors of glowworm i at the time, $d_{ij}(v)$is the Euclidian distance between glowworm and k at time t, ${r_d}^i(v)$ represents the varying nearby range of glowworm is at time v and $f_j(v)$is the updated luciferin value.

Then the discrete-time model of the glowworm movements can be denoted in the following equation

$$w_i(v+1) = y_i(v) + s\left(\frac{w_j(v) - w_i(v)}{\|w_{j(v)} - w_{i(v)}\|}\right) \tag{27}$$

Where s is the step-size and estimated as $s = \left|d_{ik} - \sqrt{3r}\right|$and $\| \ \|$ denotes the Euclidian norm operator

Neighborhood range update phase:

The updated neighborhood range of every glowworm is denoted as

$${r_d}^i(v+1) = min\left\{r_{s,} max\{0, r_d^i(v) + \beta(n_v - |N_i(v)|\}\right\} \tag{28}$$

Where β is a constant parameter and n is a parameter used to control the number of neighbors.

In the EEMRGSO algorithm, we used a reverse GSO algorithm for reducing energy consumption. The updated location of sensor i is represented b the following equation

$$w_i(v+1) = w_i(v) + (G(id) - \left(w_i(v)\right) \quad (29)$$

where $G(id)$ is the nearest grid-point location from any sensor i at time v.

Steps of GSO Algorithm

Each glowworm is considered a possible solution to the target problem in space by the GSO algorithm. Through location movement and mutual attraction, glowworms cluster to high-brightness glowworms, and several extreme points in the solution space of a target problem are identified. As a result, the issue is resolved. The following are some of its important points

Algorithm for Glowworm swarm optimization

Step 1: Initialize glowworm swarm $X = \{x_1, x_2, \dots . x_n\}$Glowworm number n in swarm, step s, fluorescein initial valueb_0, fluorescein volatilization rate ρ, domain change rate α, decision domain initial value b_0, domain threshold γmax, and other specifications required to be assigned in the initialization.

Step2: Estimate glowworm fitness depending on the objective function. Identify the fitness $f(x_j)$ of every glowworm x_j at its position related to specific objective function $y = \max(f(x))$

Step 3: Identify the movement of motion and step of the glowworm. Every glowworm x_j looks for glowworms with higher fluorescein value li within its decision radius ri, and estimate the next movements, related to fluorescein distance and value.

Step 4: Update glowworm locations. Update the position of each glowworm xi based on estimated moving direction and step

Step 5: Glowworm decision domain radius should be upgraded

Step 6: Determine the algorithm has converged or attained its higher number of iterations (itmax) and whether to proceed to the further round of iterations. By modifying the initial distribution of glowworm swarm, it can be learned that algorithm implementation can be enhanced and the premature local optimum of an algorithm can be neglected.

IV. PERFORMANCE ANALYSIS

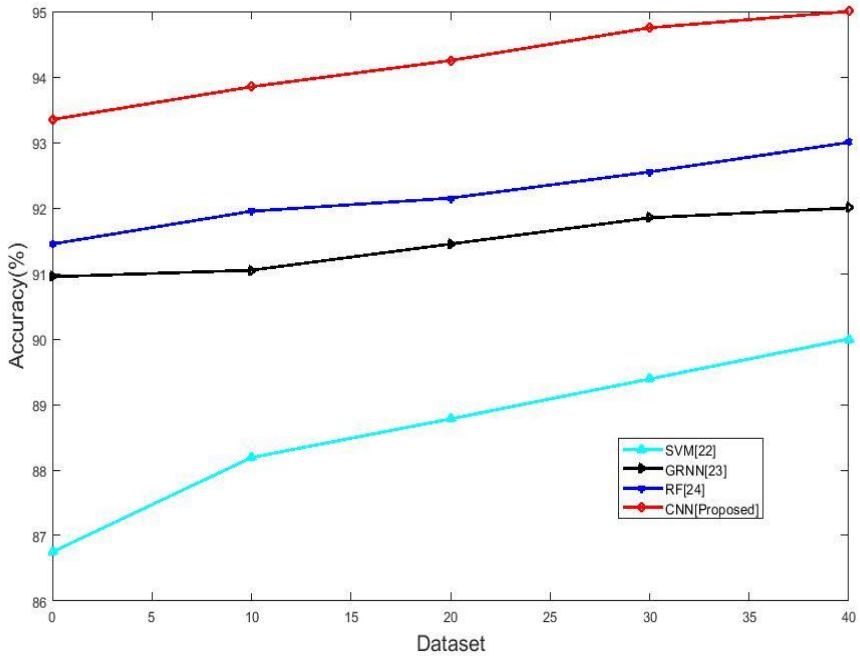
This section elaborates the results obtained utilizing the suggested approach. Numerous performance metrics may be used to analyze the performance of classification methods based on the accuracy of classification decisions. In a class variable values can be expected to be either positive (P) or negative (N) (N). The positive cases (P) that are properly categorized as positive cases by the methods are referred to as true positive (TP) cases, whereas actual positive cases that are incorrectly classified as negative cases by the methods are referred to as false negative (FN) cases. Similarly, actual negative cases (N) that are correctly labeled as negative cases by the model are considered true negative (TN) cases, whereas actual negative cases that are incorrectly denoted as positive cases by the methods are considered as false positive (FP) cases.

Accuracy:

It determines how many samples are accurately classified. It determines how closely the outcomes correlate to the original outcome.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} * 100\% \tag{30}$$

Figure 2 presents a comparative study of the accuracy for the existent and the suggested CNN-based upgraded classifier methods. The line graph shows that the proposed methodology is more accurate than the existing systems.



`Figure 2: Comparison of Accuracy (%) for existing and proposed methods

Precision:

It evaluates how precise the suggested method's performance is by analyzing the correct TPs from the anticipated ones.

$$Precision = \frac{TP}{TP+FP} * 100\% \quad (31)$$

Figure 3 shows a comparative analysis of the precision for the existent and the suggested CNN-based upgraded classifier methods. The line graph shows that the proposed methodology is more precise than the existing systems.

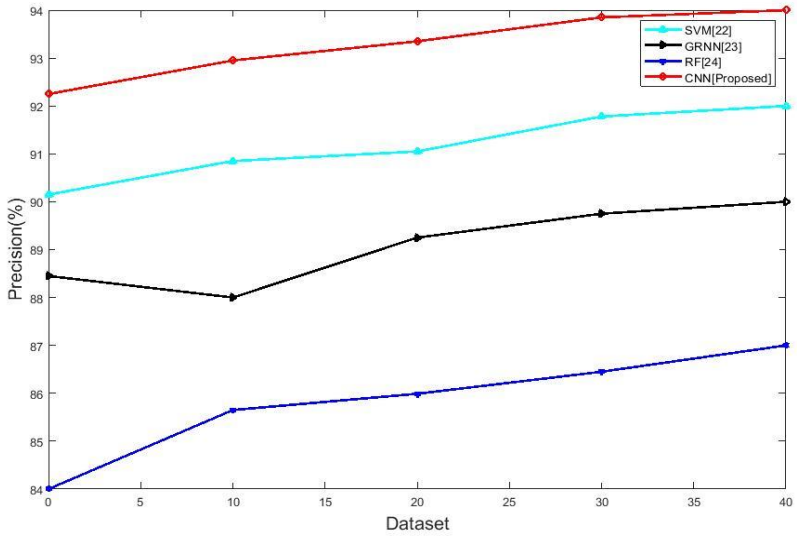


Figure 3: Comparison of Precision (%) for the existing and proposed method

Recall:

The recall is also termed sensitivity and it is the fraction of the sum of relevant samples that are obtained.

$$Recall = \frac{TP}{TP+FN} * 100\% \tag{32}$$

Figure 4 shows a comparative analysis of sensitivity for the existent and the suggested CNN-based upgraded classifier methods. The line graph shows that the proposed methodology is better than the existing systems

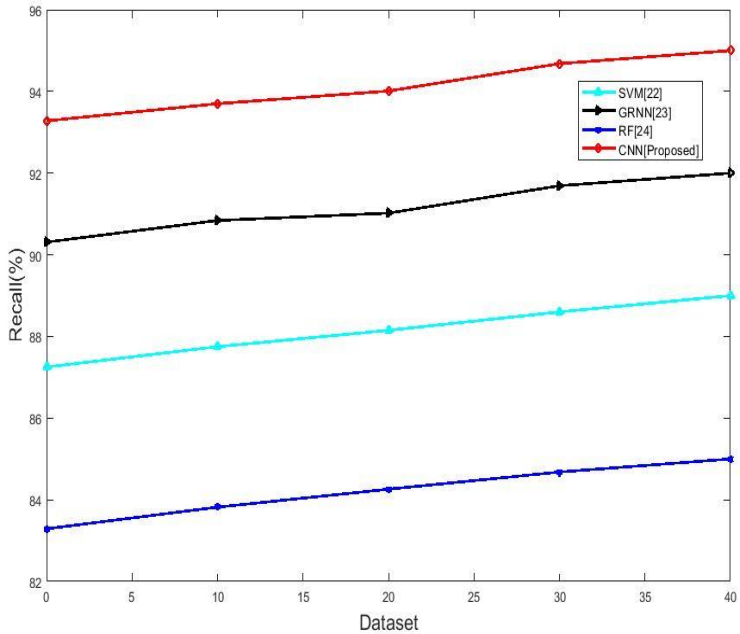


Figure 4: Comparison of Recall (%) for the existing and proposed method

$\boldsymbol{F1\ score}$ **:**

$F1\ score$ is a measure of the accuracy of the test. The F1 score is calculated by taking the harmonic mean of precision and recall.

$$f1\ score = 2 * \frac{precison * recall}{precison + recall} \tag{33}$$

Figure 5 shows a comparative analysis of F1 score for the existent and the suggested CNN-based upgraded classifier methods. The line graph shows that the proposed methodology is superior to the existing systems

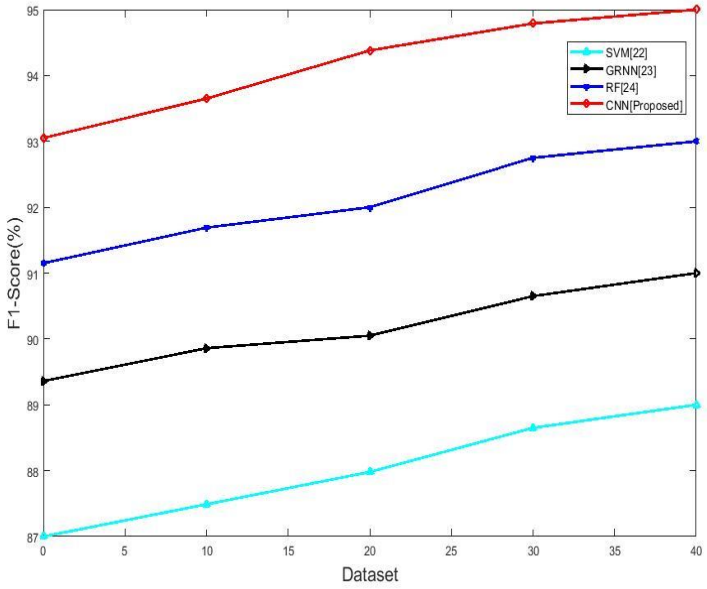


Figure 5: Comparison of $F1\ score(\%)$ for the existing and proposed method

Throughput:

The rate at which data is processed and moved from one location to another is referred to as throughput. It's a term used in networking to describe how well a network performs. Throughput is measured in bits per second or data per second.

Figure 6 shows a comparative analysis of throughput for the existent and the suggested efficient data allocation and Glowworm swarm optimization algorithm. The line graph shows that the proposed methodology is superior to the existing systems

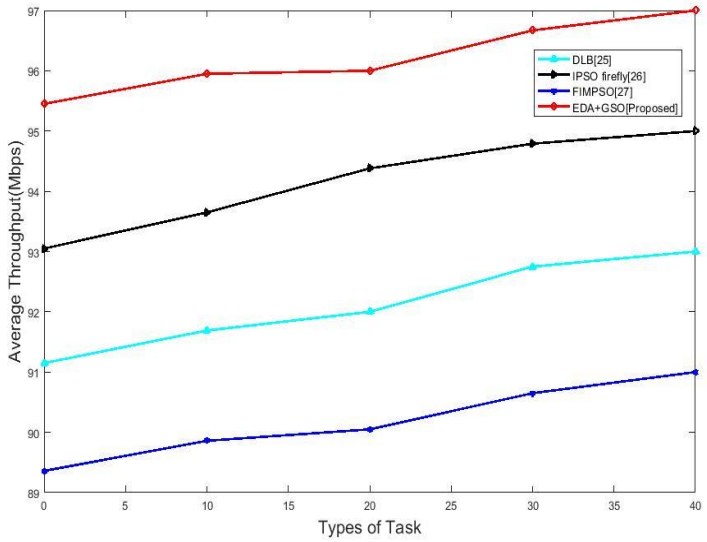


Figure 6: Comparison of throughput (Mbps) for the existing and proposed method

Memory Utilization:

Memory utilization is the fraction of the average amount of memory required to complete a task that is in use at any given time.

Figure 7 portrays a comparative examination of memory utilization for the existent and the suggested efficient data allocation and Glowworm swarm optimization algorithm. The line graph shows that the proposed methodology is superior to the existing systems

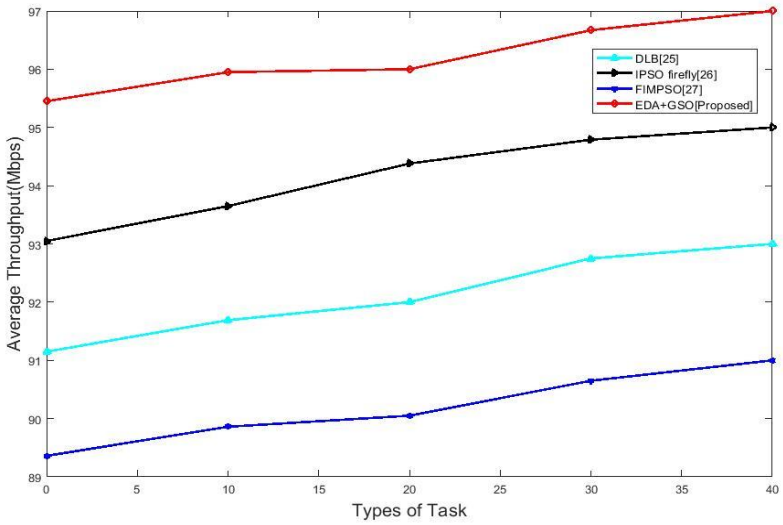


Figure 7: Comparison of throughput (Mbps) for the existing and proposed method

V. CONCLUSION

In this paper, we have suggested a unique method using a CNN-based upgraded classifier for physical education teaching and the performance metrics such as precision, f1 score, accuracy, and recall values are improved than the existing approaches. We also utilized a method for optimizing the data allocation for the resources of physical teaching using the 5G network. The Glowworm swarm optimization proposed is mainly applied for solving data object clustering problems under unsupervised learning conditions. The glowworm swarm optimization is proved to have a better clustering effect and stability. From the simulation outcome, it is understood that the memory utilization and throughput are improved than the existing approaches.

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REFERENCES

[1] Ding, y., Li, y. and Cheng, l., 2020. application of the internet of things and virtual reality technology in college physical education. ieee access, 8, pp.96065-96074.

[2] Yang, q.f., Hwang, g.j. and Sung, h.y., 2020. trends and research issues of mobile learning studies in physical education: a review of academic journal publications. interactive learning environments, 28(4), pp.419-437.

[3] Xu, l., Liu, w., Anwlnkom, t. and Jinonic, s., 2021. 6cn-driven routing and content delivery scheme for building smart physical education. internet technology letters, 4(5), p.e201.

[4]Yanru, l., 2021. an artificial intelligence and machine vision-based evaluation of physical education teaching. journal of intelligent & fuzzy systems, 40(2), pp.3559-3569.

[5] Yu, S.A., 2021. Application of computer information technology in college physical education using fuzzy evaluation theory.Computational Intelligence, 37(3), pp.1181-1198.

[6] Lei, T., Cai, Z. and Hua, L., 2021. 5G-oriented IoT coverage enhancement and physical education resource management. Microprocessors and Microsystems, 80, p.103346.

[7] Zhan, K., 2020. Sports and health big data system based on 5G network and Internet of Things system. Microprocessors and Microsystems, p.103363.

[8] Cheng, J., 2021. Evaluation of physical education teaching based on web embedded system and virtual reality. Microprocessors and Microsystems, 83, p.103980.

[9] Li, K. and Tsai, S.B., 2021. An Empirical Study on the Countermeasures of Implementing 5G Multimedia Network Technology in College Education. Mobile Information Systems, 2021.

[10] Zhu, W., 2021. Research on the Blended Teaching Mode Reform of University Physical Education Curriculum Based on the Integration of 5G Cloud Computing and Multimedia. Mobile Information Systems, 2021.

[11] Chen, S. and Liang, L., 2020. Online resource sharing of martial arts teaching based on 5G network and FPGA system. Microprocessors and Microsystems, p.103447.

[12] Sun, W. and Gao, Y., 2021. The design of university physical education management framework based on edge computing and data analysis. Wireless Communications and Mobile Computing, 2021.

[13] Du, J. and Nan, Z., 2021. Research on the intelligent model of progress in physical education training based on a motion sensor. Microprocessors and Microsystems, 82, p.103903.

[14] Xu, L., Liu, W., Anwlnkom, T. and Jinonic, S., 2021. 6CN-driven routing and content delivery scheme for building smart physical education. Internet Technology Letters, 4(5), p.e201.

[15] Wang, L., Yu, H., Cao, Y., Zhou, X., Jiang, L. and Cai, H., 2019, October. A Group-Centric Physical Education Supporting System for Intelligent Campus Application. In International Conference on e-Business Engineering (pp. 33-47). Springer, Cham.

[16] Chao, G. and Gang, W., 2021. Sports Training Teaching Device Based on Big Data and Cloud Computing. Journal of Healthcare Engineering, 2021.

[17] Kaiyan, H. and Qin, W., 2018. The development and popularisation of network platform of college sports venues in intelligent manufacturing. International Journal of Reasoning-based Intelligent Systems, 10(1), pp.20-25.

[18] Yu, L., Lu, Q., Yang, T., Wan, J., Wen, W. and Hu, D., 2021, June. Research on the Reform of Physical Education in Colleges and Universities under the Background of Big Data Era. In 2021 International Wireless Communications and Mobile Computing (IWCMC) (pp. 1519-1522). IEEE.

[19] Dong, X., 2021. Physical Training Information System of College Sports Based on Big Data Mobile Terminal. Mobile Information Systems, 2021.

[20] Sun, Q., 2020, June. Current School Sports Intelligence System Based on Artificial Intelligence and Internet of Things Technology. In International Conference on Applications and Techniques in Cyber Security and Intelligence (pp. 625-632). Springer, Cham.

[21]Awal, M.A., Hasan, M.K., Rahman, M.A. and Alahe, M.A., 2019, December. Optimization of Daily Physical Activity Recognition with Feature Selection. In 2019 4th International Conference on Electrical Information and Communication Technology (EICT) (pp. 1-6). IEEE.

[22]Jinfeng, L. and Bo, Y., 2021. Design of evaluation system of physical education based on machine learning algorithm and SVM. Journal of Intelligent & Fuzzy Systems, (Preprint), pp.1-12.

[23]Zhao, J., Guan, H., Lu, C. and Zheng, Y., 2021. Evaluation of Teachers' Educational Technology Ability Based on Fuzzy Clustering Generalized Regression Neural Network. Computational Intelligence and Neuroscience, 2021.

[24] Xu, Q. and Yin, J., 2021. Application of random forest algorithm in physical education. Scientific Programming, 2021.

[25] Mousavi, S., Mosavi, A. and Varkonyi-Koczy, A.R., 2017, September. A load balancing algorithm for resource allocation in cloud computing. In International conference on global research and education (pp. 289-296). Springer, Cham.

[26]Zhu, C., 2021. Applying edge computing to analyse path planning algorithm in college football training. International Journal of System Assurance Engineering and Management, pp.1-9.

[27] Devaraj, A.F.S., Elhoseny, M., Dhanasekaran, S., Lydia, E.L. and Shankar, K., 2020. Hybridization of firefly and improved multi-objective particle swarm optimization algorithm for energy efficient load balancing in cloud computing environments. Journal of Parallel and Distributed Computing, 142, pp.36-45.