

Retraction

Retracted: Application of Data Warehouse Technology Based on Neural Network in Physical Education Quality Management

Mathematical Problems in Engineering

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] B. Zhao and Y. Liu, "Application of Data Warehouse Technology Based on Neural Network in Physical Education Quality Management," *Mathematical Problems in Engineering*, vol. 2022, Article ID 4456885, 10 pages, 2022.

Research Article

Application of Data Warehouse Technology Based on Neural Network in Physical Education Quality Management

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Data warehouse technology has been created because of China's technological advancement and the increasing requirements of the educational sector. Physical assessments are treated as tests by many students. Institutions spend plenty of time every year through physical tests, yet the results are rarely shared with students. Teachers are impeded by the size and complexity of physical test data, finding it challenging to support experiments or judge individual students' development. Students have trouble following up and delivering test-based feedback after instruction. In recent years, various researchers have offered insightful advice on how to build multidimensional database structures for such trouble. However, quality requirements alone are not adequate to guarantee quality in reality. So, this paper presents a novel Hypertuned wide polynet convolutional neural network (HWPCNN) framework in the data warehouse technology to attain the greatest performance in physical education quality management. In this paper, we first apply HWPCNNs for physical education quality management to analyze the accuracy and recall of the model. It is no secret that HWPCNN is now one of the most widely used deep learning techniques. When it comes to managing the quality of physical education, the HWPCNN's local perception feature in the data warehouse technology allows it to achieve the best possible results. To validate the model's performance, it is compared to other models and then improved further to increase its accuracy. The physical education resources are gathered as a raw dataset for this inquiry. The raw dataset is cleaned using the Z-score approach to get it ready for further data processing. Then, a sparse matrix approach is employed to build a data cube, while the proposed method is used to index multidimensional databases. To demonstrate that our work is of the best quality in managing physical education, performance metrics of the suggested method are also evaluated and compared with other traditional methods.

1. Introduction

The new health-oriented Physical Education (PE) curriculum, which places more emphasis on health promotion and regular physical activity engagement than it does on athletic performance, presents a new challenge for physical education teachers. Specifically, the challenge lies in the fact that the new health-oriented PE curriculum. The health information of students has to be monitored during both practice and competition to build effective training routines and reduce the risk of accidents and illnesses. Large volumes of nonvolatile, summarized, and historical data may be stored,

managed, and analyzed using data warehousing (DW). Data warehouses are multidimensional repositories that collect students' physical data from a variety of systems into a single repository. The primary goal of DW is to help organizations have a better understanding of their performance and make better decisions. Data analytics (DAs), as well as online analytical processing (OLAP), are areas that examine the physical data in this database in cooperation with one another. Data analysis (DA) is the process of employing technical and statistical tools to analyze the physical data in the DWH to conclude and generating new knowledge from the data [1]. The "Extract, Transform and Load (ETL)" is a

critical building component of a DW since it extracts students' data from sources, fixes existing errors in the data integrates the data to meet the model of a target DW and loads it into a DW. For example, commercial and open-source models, relational and nonrelational databases, and technologies may all be used by the sources. The ETL procedure is the most time-consuming part of a data warehouse's development life cycle. ETL transformations may include one-to-one, many-to-one, and many-to-many mappings, as well as a variety of other mappings. This may result in inaccurate analytical findings as a consequence of faulty ETL implementations, which can be exacerbated by complicated transformations. The need of testing ETL procedures to guarantee reliable extraction and transmission of original data into storage systems cannot be overstated [2]. To support their judgments, educational staff members use a variety of tools and apps, including DSSs, mobile learning, and web-based tools like information extraction, which are all based on distinct techniques and approaches. This time around, the findings and inferences that may be taken from prior studies and in-depth analysis have more of an impact and are more legitimate than they were in the past. Online analytical findings are provided by the Educational DW, which is the best alternative for all educational leaders. Educational DW gives a broad overview of the student's performance and enables them to identify the roadblocks on their path to success. A large educational DW may be used to implement any strategy or technique that applies to a small one. Educational DW may successfully eliminate educational mistakes that impair academic decision-making [3].

Figure 1 depicts the holistic perspective of DW in education. Data Warehousing platforms traditionally used by organizations face many difficulties, including bottlenecks in the collection of students' physical data as well as the analysis techniques of that data. These bottlenecks are due to the increasing number of "information efficiency," "scalability," and "elasticity" that can only be obtained through parallel storage and processing. All data marts are loaded from the same DWH, therefore they all share the same consistent dimensional representation of data. Because it takes a bird's-eye view of the company, the top-down method lends itself well to change management. On the other hand, is advocated for when resources are limited, and data marts are built in stages. Strategic priorities gleaned from an information requirement analysis may guide the development and deployment of data marts. The goals of the organization, the structure of the company, the available funds, and the interdependencies across departments all have a significant bearing on the strategy that should be used while developing a DWH for an educational institution. A comparison of the two methods is shown schematically in Figure 1. The ETL procedure of the top-down method is shown in Figure 1; in this procedure, data is taken from both internal and external data sources. Afterward, operations like cleaning, scrubbing, and deduplication are carried out to alter these data sets. Clean data are then put into a centralized DWH before being partitioned into data marts for various business units [4]. Standard DWs have a stringent modeling approach, which further underscores the need for a "Big Data Warehouse

(BDW)." Despite this, the current state of BDW demonstrates the concept's youth, uncertainty, and lack of standard techniques for building BDWs [5]. Data is being gathered from all around the globe and stored in the massive data warehouse (DW). For operational processing and issue solving, DW divides data sets and programs into two distinct categories: data sets used for operational processing and those utilized for analysis. Historical layers may be included in the preaggregated and preintegrated data. When it comes to data warehouses, invariance and low redundancy are the most important characteristics. With today's DWs, management can make choices based on almost endless volumes of very accurate data, which helps firms avoid a variety of issues. Each significant corporation retains and deploys new DWs. The issue is that DWs are expected to become more expensive to build, support, and maintain. This research evaluates the application of DW technology based on a neural network in Physical Education Quality Management. The Contribution of the research work is depicted as follows:

- (i) This study selected a raw dataset of physical education materials from China university students
- (ii) The Z-score technique is used to clean the raw dataset in preparation for future data processing
- (iii) To construct the data cube, a sparse matrix is used
- (iv) To index multidimensional databases, Hypertuned wide polynet convolutional neural network (HWPCNN) is used

The other portion of this study is divided as follows: Section 2 depicts a literature work. Section 3 includes the suggested approach. Section 4 illustrates the result and discussion. Section 5 depicts the conclusion.

2. Literature Work

Wyant and Baek [6] explore variables that impact physical education instructors' acceptance of technology in teaching, detail how decision-making research may educate the technology acceptance processes, then give a guidance document to increase technology adoption among physical education teachers. Interactive virtual technology for college physical education that integrates the Internet of Things (IoT), a compute cluster, as well as a mobile application, is described by Ding et al. [7]. A 12-year-old girl was found to have many odontogenic keratocysts on her teeth [8]. Data properties and query statistics are taken into consideration in Tomashevskiy et al. [9], the scientific and practical challenge in establishing information technology for hybrid distributed databases [9]. Salaki and Ratnam [10] analysis in Higher Education shows the value of Agile Analytics in the creation of "Business Intelligence" and DW. According to Cigánek [11], an open DW uses data from a variety of sources. They explain the principles of data warehouses, as well as the reason for open data. Sutedia et al. [12] examined and construct a data warehouse for integrating multiple operational databases required to offer data on XYZ University's active students. According to Garg [13], digital approaches were used to connect physical objects and depict

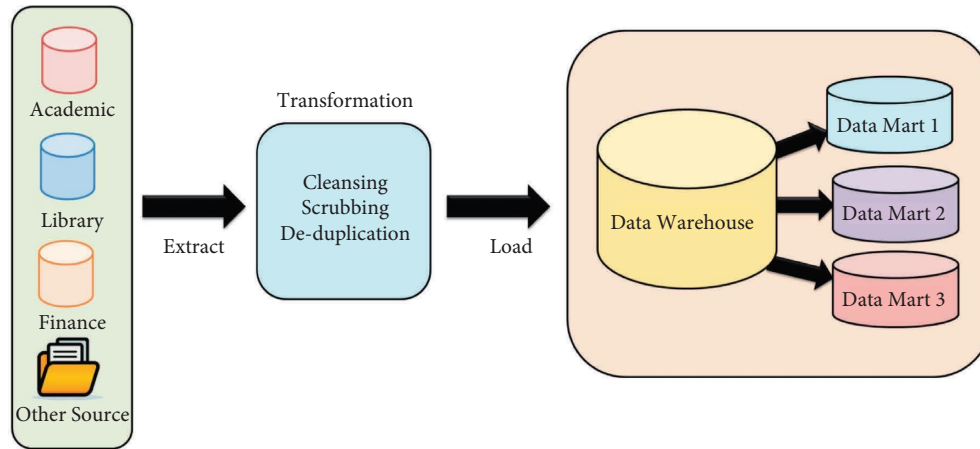


FIGURE 1: A holistic perspective on DW in education.

their current status. According to Sebaa et al. [14] and Ahmed and Ali [15], an overview of typical data warehouse research topics is presented as well as several noteworthy Hadoop-based data warehouses. Shahabzand and Afzal [16] examined how semantics may be used as a tool to connect data warehouses, NoSQL databases, and big data in a meaningful manner. The developments in data storage and processing evolved to manage large data but also pushed conventional, previously existing systems out of focus and created a divide between the old and the new. Garani et al. [17] described the data warehouse schema in a way that integrates temporal and geographical data in an all-encompassing data warehouse architecture. It is becoming more vital to integrate time- and space-based data. Li [18] present a hybrid network system for “business intelligence,” “analytics,” and “knowledge management” based on an educational DW and a service design repository that empowers the advancement of knowledge and the visualization and outline of dissimilar organizational components. Following “Satya Wacana Christian University (SWCU)” financial and educational data, according to Somya et al. [19], the SoBI will be used to integrate DW. According to Salihuan and Zayyanu [20], the development of a college sports training aid decision-making support system is based on the use of data warehouse and data analysis technology to realize various aspects such as university students’ controller is developed, innovative training methods used in university sports management, and combined User input to generate a sensible sports training program.

3. Proposed Methodology

When Devlin and Murphy (1988) came up with the idea of a “data warehouse (DW)” for storing corporate information, they sought a read-only database that would allow customers to look at and access the data for use in making choices. Later on, the term “subject-oriented,” “integrated,” “time-variant,” and “nonvolatile” were added to the definition of DW. Even if this data is summarized and detailed, each of these studies admits that since DW can physically separate information from operational databases, it offers a way for

real-time decision-making that is quicker than without DW. As a result of this recognition, DW has emerged as a key hub for decision support inside organizations. HWPCNNs are among the most popular deep learning methods. The data warehouse technology used by the HWPCNN permits it to provide optimal outcomes in the management of physical education quality. The model’s efficacy is established by comparison to benchmarks and it is then refined to achieve higher levels of precision. Figure 2 illustrates the suggested approach flow.

3.1. Physical Education Dataset. Second-year pupils at a university in central China that participated in the “Basketball Club” option of a mandatory PE program were the subjects in this data analysis. The instructor in charge of the club was a member of the faculty in the department of physical education and had been active in this club system for the past three years. An additional faculty member was assigned to teach novice players, while physical education majors aided with refereeing tasks to support them. This research did not gather any information from the support staff.

When they arrived for their first lesson, students were given a short report to complete, which allowed them to gather information about their prior basketball experience, their estimation of how good they are at the sport, and why they chose it. An overview of the data for these participants may be seen in Table 1.

3.2. Data Preprocessing Using Z-Score Normalization. In operations, each user’s data is sized individually. The quality of the original data may be affected if grouping is done using that data. An excellent technique to improve data accuracy is to convert all data to a single scale. To standardize all data, the Z score normalization procedure is used. The Z-score normalization formula may be found in the following equation:

$$Z = \frac{X - \mu}{\sigma} \quad (1)$$

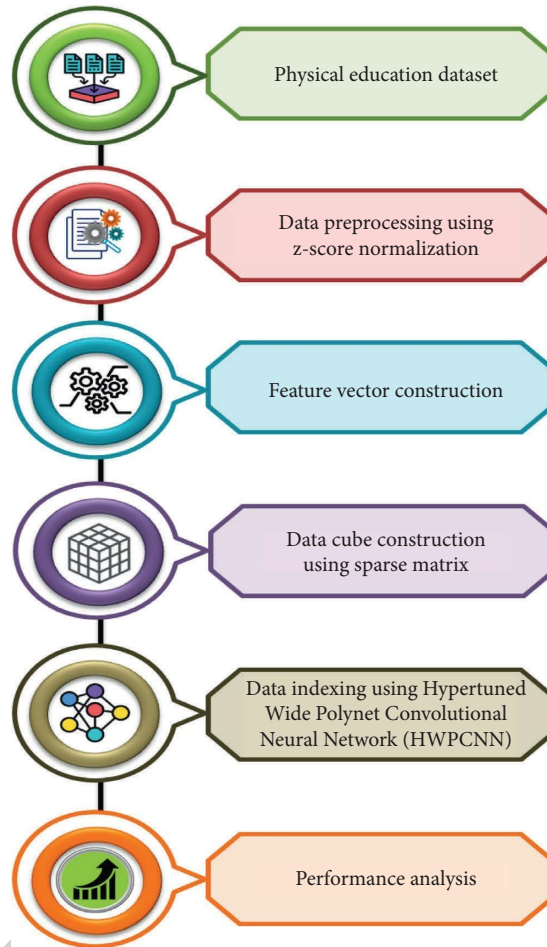


FIGURE 2: Flow of the suggested approach.

TABLE 1: Data for students [21].

Gender (<i>n</i>)	Sport education		Individual practice	
	Female (47)	Male (55)	Female (21)	Male (29)
Age (%)	19.3	19.4	19.4	19.4
Experiences (%)	None (13)	None (11)	None (25)	None (15)
	Some (54)	Some (17)	Some (45)	Some (59)
	Regular (33)	Regular (71)	Regular (30)	Regular (26)
Skill (%)	Medium (26)	Medium (20)	Medium (16)	Medium (4)
	Entry level (64)	Entry level (34)	Entry level (47)	Entry level (83)
	Novice (10)	Novice (40)	Novice (37)	Novice (13)
Why basketball (%)	Learn (18)	Learn (15)	Learn (19)	Learn (12)
	Fitness (10)	Fitness (11)	Fitness (19)	Fitness (21)
	Love (13)	Love (0)	Love (0)	Love (0)
	Interest (59)	Interest (74)	Interest (63)	Interest (67)

In this example, Z is the data value's normal frequency. X stands for providing practical numbers of characters that have a special connection. μ is the average of the functions of user operations that are comparable. There is a zero-to-one variation in Z score normalization's overall average. σ is a

variation of the distribution data warehouse concept. The average variance is calculated using the following equation:

$$\sigma = \sqrt{\left(\frac{\sum (X - \bar{X})}{g}\right)}. \tag{2}$$

Vendor operations quantities, X , make up the rest of the world's technical quantities. Overall, a variable's total score is calculated (X). In all, g samples of physical data were collected from vendors for this study. Distributor distribution test data, standardized average, as well as frequency data, are utilized to calculate a Z score for a distributor distribution test dataset.

3.3. Feature Vector Construction. When using a self-organizing network, an input matrix is generated that contains the parameters specified by the dimensions. Input parameters are prepared by selecting dimension values. Key values are allocated numeric values based on the character reference table for each dimension. Key value parameters are defined by using this data. Self-organizing networks may use these parameters as input.

Self-organizing networks may use these parameters as input. Each time a winning neuron receives an input; its neighbors' weights are adjusted to reflect the new information. The final weights for each dimension of the self-organizing net are saved when training and testing are complete. Weights will be applied to indices at the time of data access to arrive at these results. The active neuron index numbers for each dimension are gathered. In other words, they are the values' indices. To avoid index values colliding, the self-organizing net is used, and the indices created during training are arranged in the same order as the dimension values. MOLAP cube creation will take into account each dimension's index number. This will also be the best option for storing things once we are not used.

3.4. Data Cube Construction Using Sparse Matrix. Analyze each data one by one in the fact database to acquire tuple-specific indexes. Then, put the fact values at those indexes. Due to the sparsity of multidimensional data cubes, index values for nonnegative cell entries are stored in sparse matrices. To store indexes of three-dimensional values, we need to define a sparse structure with three variables, and a fourth to store the matching values. One tuple is stored in a single instance of the sparse structure. The term "defined array" refers to a structural array that has a size that is equal to the number of records in a fact table. Fact tables are examined one by one, looking at each tuple and calculating the measured value for each dimension to put it into a sparse structure. Dimensional weight matrices are used to construct indexes for dimensional data. Each node in the self-organizing net is assigned a final weight value once the weight matrices for each dimension have been stored. We may use the multidimensional character reference server's numerical values of characters to generate an input vector that can be used to retrieve the index of any dimension value. A weight matrix of that dimension determines the Euclidean distance of this vector from each self-organizing network node. For each dimension, the cluster index number created is the index. In the sparse structure, each tuple's index value is computed and stored in the same place as the corresponding measure value. The sparse structure array may now hold the whole matrix. Table 2 depicts the data cube in the sparse matrix.

TABLE 2: Data cube in sparse matrix.

Physical education resources	Products	Year	Value
1	3	10	36596.23
1	3	8	19496.45
1	2	10	6803.54
1	2	9	571.40
1	2	8	11321.19
1	2	7	2669.1
1	2	6	2581.02
1	2	7	7723.14
1	1	6	15.29
1	1	5	12.15
1	1	4	7.16
1	1	3	5.05
1	1	2	0.0
1	1	1	8579.62

This design shows that each cube dimension corresponds to a tuple in the fact table. Each data row cube contains a single tuple, making it a sparse structure. All of the records in the fact table are represented by a single instance. There are several instances of the multidimensional array-based sparse data cube for each cell carrying the value of a tuple in the multidimensional array. As the number of the tuple's in a sparse structure rises, it will be easier to split the fact table contained in the sparse structures by taking each tuple in one instance of a sparse structure. All of the dimensions are represented in the data cube shown above. To store the whole data cube, you will need a lot of storage space. Many aggregates are recomputed by decision support systems to speed up aggregation queries. It is feasible to calculate aggregates along all conceivable group-bys in a data cube. Data cubes must be kept in front of group-bys for a fast data retrieval system. $2^N - 1$ aggregate calculations are needed for an N -dimensional data cube. In the above case, there are three dimensions and one measure value so $2^3 = 8$ group-bys are calculated as {Physical education resources, Products, Year}, {Physical education resources, Products}, {Physical education resources, Year}, {Products, Year}, {Physical education resources}, {Products}, {Year}, and all. The term "data cube" is used to describe a collection of group-bys. There are two formal routes to group-bys before sparse cube creation. A sparse structure may hold both the fact table and all the views of the fact dimensions. The enormous memory needed makes this approach prohibitively expensive. Second, the sparse data cube that was generated from the original fact table may be used for aggregation along dimensions, and the resulting group-bys will also be saved in the sparse structure. Any group-by will be computed by selecting the smallest of the previously computed group-bys as its parent. In the above-given data cube, the cardinalities of the dimensions are 100, 101, and 11 for Physical education resources, Products, and Year, respectively. The original data cube will be used for calculating group-bys {Physical education resources, Products}, {Physical education resources, Year}, and {Products, Year} from these group-bys the group-bys {Physical education resources}, {Products}, and {Year} are computed using {Physical education resources, Year}

and {Products, Year} as they are smallest parents for these aggregates or group-bys. Similarly, supper aggregate all is calculated from parent group-by {Year}. These group-bys are used for and kept in sparse structures for aggregation queries are quick to obtain since they do not need data from the original data cube. In addition, less memory is needed to store these group-bys.

3.5. Data Index Using Hyper Tuned Wide Polynet Convolutional Neural Networks Algorithm (HWPCNN). A distinct index is created for each dimension when working with a multidimensional database. As a result of the clustering of the data, related data values are clustered together into various groups. The dimension's number of occurrences is not predetermined. Unsupervised learning makes clustering ideal for dimensional data indexing. In this research, for both classification and regression problems, hyper tuned wide polynet convolutional neural networks algorithm neural network technique is used. HWPCNN uses convolution layers to choose between accuracy and latency for parameter values, which is a simpler framework to understand and apply to real-world problems. The HWPCNN technique has a key advantage in that it minimizes the network size. A quantized configuration that analyses a common problem difficulty in depth via many abstraction layers seems to be the underlying structure of software. Modeling platforms use a common rectified linear unit (ReLU) to point across different abstraction levels. The dimensions and internal representation of each layer may be reduced by increasing resolution by w .

Residual layer with stride 1 and second decreasing layer with stride 2 in this design. There are three sublayers to the two primary layers: residual and shrinking. ReLu6 was used to construct a 2×2 convolution as the first layer. Convolution is the next phase in the design process. Depth-Wise may benefit from a single convolutional layer for light filtering. None of the proposed architecture's three convolution layers have any nonlinearity. When it comes to output, the ReLu6 component plays a key role. ReLu6 enhances the model's unpredictability under low-precision settings. The number of output channels does not vary at any point for the whole of the sequence. During the training phase of contemporary architectural models, dropout and batch normalization are both used. These models employ a filter with a size of three by three. Because the activation component of ReLu6 has a residual component, batch processing is simplified by using this component.

$$Y = \{(y_1.a_1), (y_2.a_2), \dots, (y_n.a_n)\}. \quad (3)$$

If we have a feature vector map of size Y , we may refer to the input variable as l and the output variable as m . In other words, l represents the input and m represents the result. For the sake of the neural network's input patterns, the values of the data are represented as dimensional feature vectors. The following equation may be used to arrive at an estimate of the total amount of computational work required by the fundamental abstract layers of the design.

$$Y = \frac{1}{axz} \sum_{s=1}^a \sum_{w=1}^z \phi UN(s, w). \quad (4)$$

The probability of index multidimensional databases can be identified using the following equation:

$$J(\beta) = \frac{1}{N} \sum_{i=1}^n \text{classify}(h_{\beta}(x^{(i)}, y^{(i)}), \quad (5)$$

$$J(\beta) = \frac{1}{N} \sum_{i=1}^n \text{classify} \left(h_{\beta} \left(x^{(i)}, y^{(i)} + \frac{\lambda}{2N} \sum_{j=1}^n \beta_j^2 \right) \right).$$

In the same manner, anomalous feature estimators are used to numerically optimize the equation [6],

$$f(Y1) = y, \dots, y_n | a_1, \dots, a_n. \quad (6)$$

Then, the trust value of the data was calculated.

$$C_{tv} = (C_{n_fea} \text{ dist corr}). \quad (7)$$

Here, C_{tv} denotes the data's trusted value. Use this kind of neural network architecture to group input patterns and the data values of each dimension are used as the clustering data set for indexing multidimensional databases based on the features of a specific data collection. Since the dimension's cardinality is unknown at all times, data are updated at a set interval in a data warehouse. It is expanding at an astronomical pace. An indexing system does not need any additional effort to add more data values. Consequently, a new indexing system must have this capability.

4. Result and Discussion

In this section, the results of applying data warehouse technology based on neural networks to the management of physical education quality are discussed. Eleven metrics are taken into consideration to examine the efficacy of our suggested HWPCNN technique as well as the implications of the proposed features. These metrics are as follows: "true positive rate", "false positive rate", "true negative rate", "false negative rate", "f1 score", "accuracy", "precision", "f1-score", "specificity", "MAE", and "ROC", "k-Means Clustering and Genetic Algorithm based Optimized Case-Based Reasoning Approach (kMC-GA based OCBRA)", "Backtracking Search Optimization Algorithm (BSOA)", "Modified Artificial Bee Colony algorithm (MABCA)", and "Manhattan Frequency k-Means (MFk-M)" algorithm are some of the existing methods that are compared to our proposed method. Four elements will be considered in this evaluation:

True Positives (t_p). The actual and expected class values are both positive, which indicates that these values have been accurately recognized as positive

True Negatives (t_n). These estimated negative values are genuine, which suggests that the typical class value is negligible and the projected class value is also nil

False Positives (f_p). There is a discrepancy between the projected class and the real class

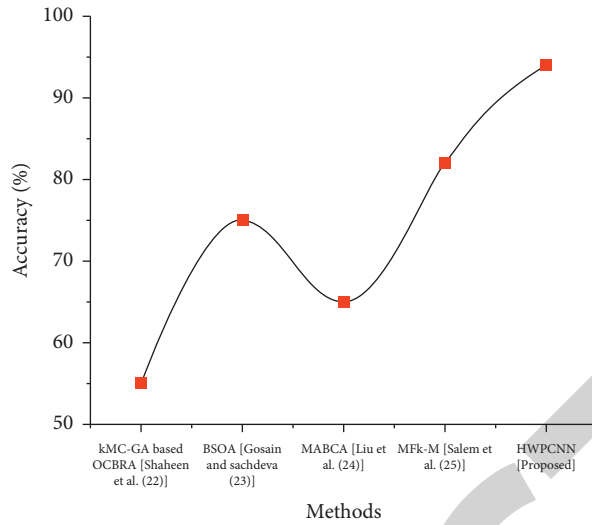


FIGURE 3: Comparison of the accuracy.

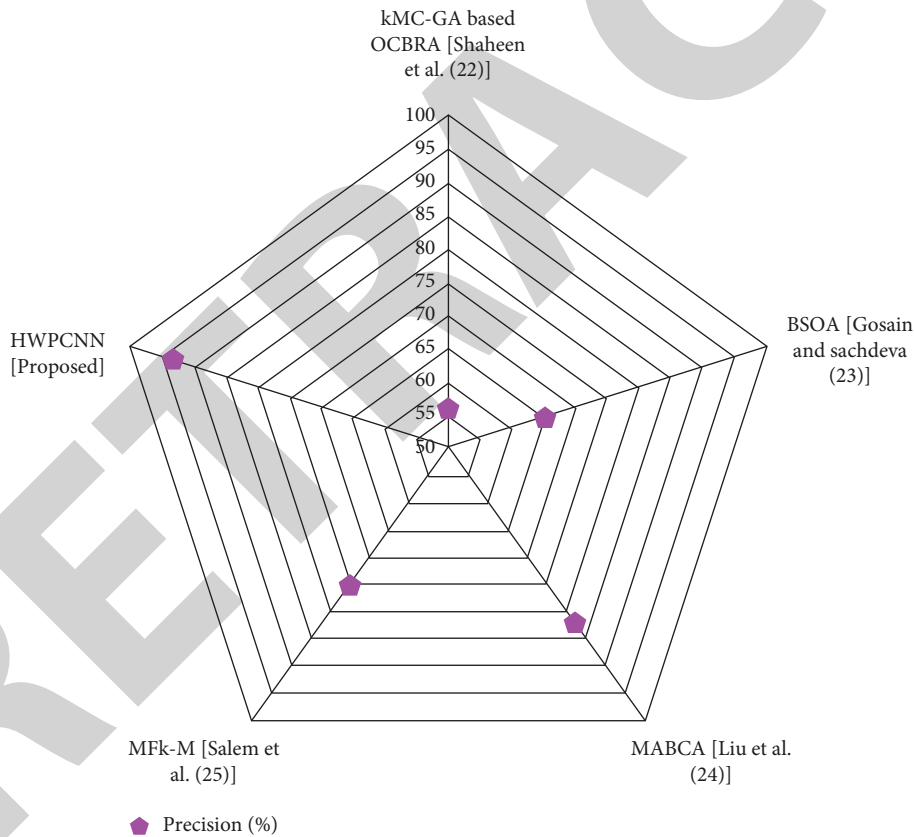


FIGURE 4: Comparison of the precision.

False Negatives (f_n). Any time the real class matches the projected one, although the predicted one does not match

Accuracy, the metric that makes the most intuitive sense, is explained as the ratio of properly expected observations to the total of observations. The accuracy of the suggested method is compared to that of the method that is currently being used in Figure 3. The proposed method had a higher

average accuracy than the existing methods. Accuracy is calculated by using the following equation:

$$\text{Accuracy} = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{8}$$

Precision is the ratio of correctly predicted observations to the total of all predicted positive observations. The precision of the suggested method is compared to that of the

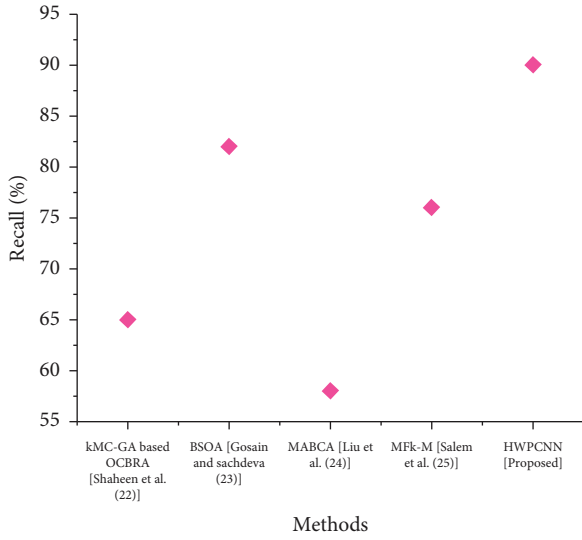


FIGURE 5: Comparison of the recall.

method that is currently being used in Figure 4. The proposed method had a higher precision than the existing methods. Accuracy is calculated by using the following formula:

$$\text{Precision} = \frac{t_p}{t_p + f_p}. \quad (9)$$

“Recall” refers to the fraction of correctly anticipated positive observations in a class. The recall of the suggested method is compared to that of the method that is currently being used in Figure 5. The figure clearly shows that the suggested method is superior to the conventional techniques in terms of recall. The recall is calculated by using the following formula:

$$\text{Recall} = \frac{t_p}{t_p + f_n}. \quad (10)$$

Precision and Recall are weighted together to get the F1 Score. The F1-score of the suggested method is compared to that of the method that is currently being used in Figure 6. The figure shows that the proposed method is higher than the conventional techniques in terms of the f1-score. F1-score is evaluated by using the following formula:

$$F1 - \text{score} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}. \quad (11)$$

True negatives that are accurately anticipated by the mode are known as specificity. The specificity of the suggested method is compared to that of the method that is currently being used in Figure 7. The figure shows that the suggested method is better when compared to the traditional techniques in terms of specificity. Specificity is calculated by using the following formula:

$$\text{Specificity} = \frac{t_n}{t_n + f_p}. \quad (12)$$

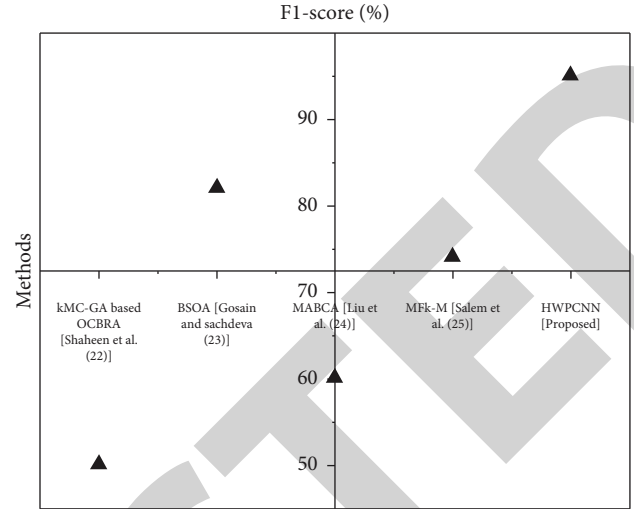


FIGURE 6: Comparison of the F1-score.

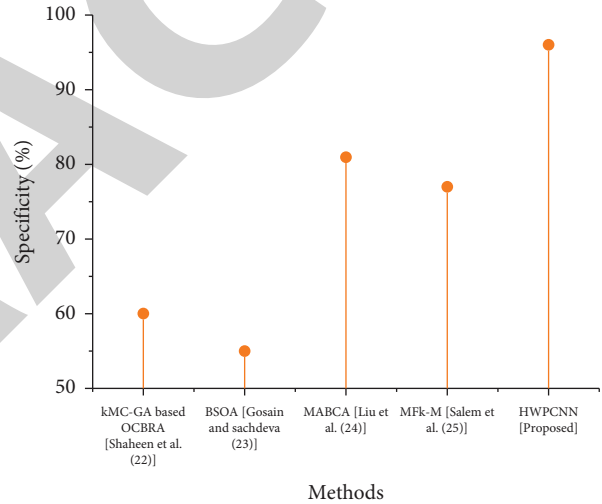


FIGURE 7: Comparison of the specificity.

A measure of the errors that occur between paired observations that both describe the same phenomena is called the mean absolute error (MAE). The MAE of the suggested method is compared to that of the method that is currently being used in Figure 8. The figure shows that the suggested method is lower when compared to the traditional techniques in terms of MAE. MAE is calculated by using the following formula:

$$\text{Mean Absolute Error} = \frac{\sum_{j=1}^m |x_j - y_j|}{m}, \quad (13)$$

where x_j denotes prediction, y_j denotes true value, and m denotes the total number of data points.

False positives (FPs) and true positives (TPs) are represented by the receiver operating characteristic (ROC). Because it accurately identifies all positive and negative instances, (0, 1) is the best classifier in the ROC plot. The ROC of the suggested method is compared to that of the

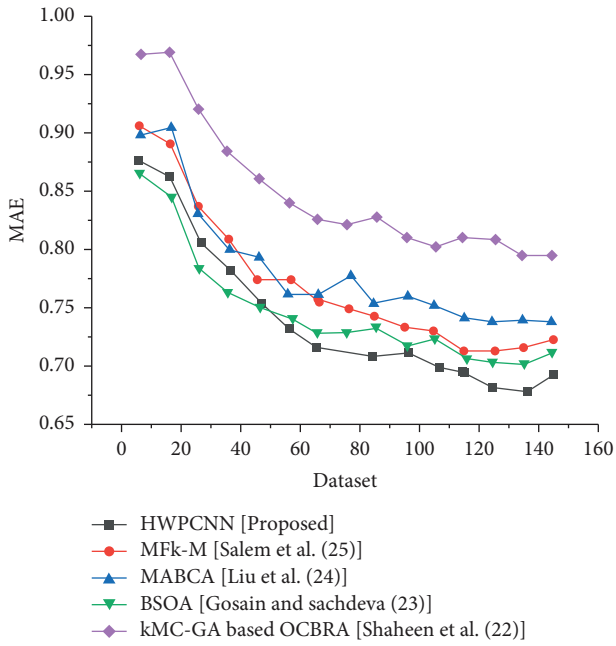


FIGURE 8: Mean absolute error.

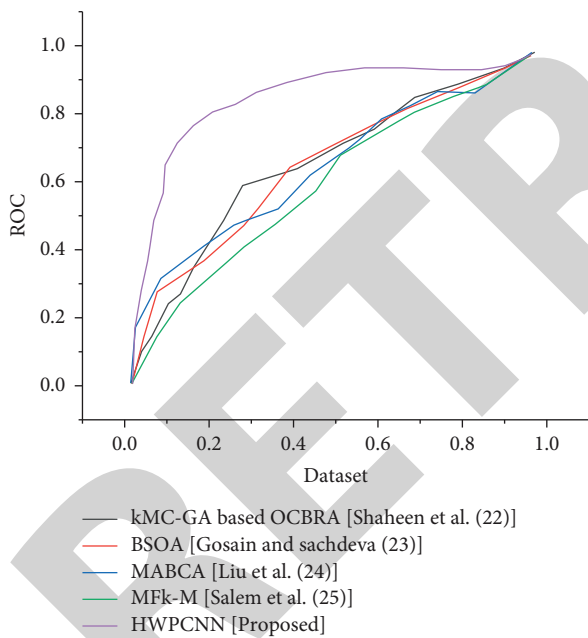


FIGURE 9: Receiver operating characteristic(ROC).

method that is currently being used in Figure 9. The figure shows that the suggested technique is far better when compared to the traditional techniques in terms of ROC.

5. Discussion

This study discovered that the deployment of data warehouse technology needs the support of top-quality management, as this is a prerequisite for a program to receive the essential Physical education resources for success. Figures 3–9 display the comparison of the suggested

approach with that of the existing method. The figure demonstrates that the suggested technique outperforms the existing methods because of the following shortcomings of existing methods. kMC-GA based OCBRA approach is expensive and hence it is difficult to implement, BSOA is easy to fall into local optimum, MABCA suffers from incorrect exploitation in addressing intricate issues, and MFk-M has the challenge in clustering data when clusters are of various sizes and densities. There is a need for improvement in the system’s resilience regarding indexing since there are situations in which creating the correct index of that key value is impossible if the value of the lost character is the highest in the character reference table. This limitation demands more research. Since only the final weight matrices from the conditioned neural network are maintained, the space requirements of the resulting indices are minimal. Final weight requires less space than hash tables. Implementation, Proposed Schema, Data Analysis, Efficiency, Effectiveness, Business Needs, and User Needs. Based on our research, we’ve discovered several key aspects of successful DWH initiatives and proposed a five-step process for creating your DWH for use in your endeavors. [22].

6. Conclusion

Decision-making in any corporation depends on the quality and management of data in physical education. Data quality and management challenges resulting from the physical education material source systems must be addressed by organizations. In addition, data quality and management are not only about identifying and correcting data quality problems. A DW and any other systems dealing with data gathering, storage, and analysis are also critical to the success of business operations. We proposed a novel HWPCNN approach to index multidimensional databases in PE quality management. Our proposed method achieves an accuracy of 94%, precision of 93%, recall of 90%, F1-score of 95%, and specificity of 96%. This study focused on only one China government department, and only at the head office level. There are numerous China government departments and most exist at national, provincial, regional, and local levels. Conducting future research into a data warehouse in physical education quality management and at only one level, that is, the national level, maybe neither a good representation of other government departments nor of other levels.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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