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THE EVALUATION MODEL OF PHYSICAL EDUCATION TEACHING PERFORMANCE BASED ON DEEP LEARNING ALGORITHM

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Abstract. The various manifestations of physical education instructional elements and assessment ambiguity affect both the qualitative and quantitative evaluation outcomes of instructional effects. An evaluation approach of physical education teaching and training excellence based on deep learning is developed to address the issues of high complexity and low accuracy in the assessment of physical education teaching outcomes. The construction of the system of evaluation indexes is predicated on the instructional material, teaching behaviour, instructional resources, teaching technique, and learning impacts that impact the quality of instruction. The model for the assessment of the physical education learning effect was created using the Genetic Algorithm-Back Propagation Neural Network (GA-BPNN) to increase the assessment accuracy of the teaching effect. The monitoring of the entire teaching process is the foundation of the assessment approach. The general objectives and a chosen set of three-level indicators for evaluation were examined considering the different types of physical education teaching variables and the assessment's degree of uncertainties. The hierarchical structure was created using the (GA-BPNN) method, which also produced the hierarchy's overall rating and comprehensive score. According to the test results, the teaching assessment model developed in this work has an Accuracy, which is higher than the industry average and supports improving the quality of instruction.

Key words: physical education, teaching, deep learning, hierarchical structure, education instructional elements

1. Introduction.

Physical education teaching exercises serve as the primary means of putting physical education into practice. Reforming schooling is a top priority for the Ministry of Education. To further promote teaching reform, it is emphasized in the new curriculum standards released in December 2011 that the educational standards should serve as the primary foundation for instruction. Every community ought to actively assist teachers in planning lessons in strict compliance with requirements for the curriculum, understanding their ability to teach and challenge, actively modifying concepts and behaviours, considering the development and enhancement of students' learning responsibility and excitement, and trying to manage their workload [7, 21, 9]. Thorough research on the teaching of physical education is needed in this environment.

The improvement of high-quality education has gained increasing attention as society advances more quickly. The study and advancement of physical education (PE) teaching reform in schools is ongoing. A growing number of experts and academics place a premium on the caliber of instruction provided in the classroom [20, 19]. To rapidly ascertain pupil attendance and educational status, intelligent teaching schemes integrate recognition of facial features, recognition of gestures, and online learning behavioural analysis technologies into both traditional classroom settings and virtual learning environments. Then, to help educators and learners make the most of the current resources and swiftly arrive at the best outcomes, a smart system for instruction can be developed [22, 12]. Positively, PE instruction in schools has seen a steady increase in the popularity of many sports over the last ten years.

Physical education instruction places a strong emphasis on the autonomous cooperative inquiry teaching approach and views student engagement with material, context, and understanding as an essential component of learning [1]. The primary goal of physical education curriculum is to help pupils develop the fundamental skills necessary for major learning. Examples include the development of students' abilities, strategies, and motion execution excellence; the enhancement of sporting classroom education; and the development of students' attitudes toward sports, sporting expertise, and interpersonal skills in sports [18]. The impact of physical education on instruction varies greatly throughout China.

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Teachers, who are the focal point of the classroom, have a duty to consider students' learning while making judgments. The opinions of students ought to be highly valued and supported. It's important to consider and honour the unique needs, skills, and developmental stages of each learner [6]. The term "teaching effect assessments" refers to the process of further concretizing the initial, more abstract construction objectives, task specifications, and evaluation requirements to create a quantitative structure that can be utilized to measure, examine, and even precisely assess how curriculum teaching is developing [5]. The main contribution of the proposed method is given below:

1. The study combines genetic algorithms (GA) and a back propagation neural network (BPNN) to present a novel evaluation model for evaluating physical education teaching performance.
2. This combination provides an extensive instrument for educational assessment by combining the powerful learning skills of BPNNs with the worldwide optimization abilities of GAs.
3. The study shows how well an algorithm based on genetics works when used to optimize the neural network's hyperparameters. By drastically cutting down on the period and difficulty required for individual variable selection, this method creates a more accurate and efficient evaluation procedure.
4. In comparison to conventional techniques, the study obtains a greater accuracy in teaching assessment of performance by utilizing the combined GA-BPNN model.
5. With the help of the comprehensive analytics on performance indicators that the GA-BPNN model offers, administrators and educators may better understand the effectiveness of their instruction and pinpoint areas in need of training and professional development.

The intricacy and variety of educational components in the field of physical education, along with the inherent uncertainties in evaluation procedures, provide formidable obstacles. The evaluations of educational results, both qualitative and quantitative, can be greatly impacted by these complications. Assessments produced using traditional approaches frequently fall short of adequately reflecting the complex dynamics of physical education environments and the actual quality of instruction or learning results.

Goal of the Research. The main goal of this research is to improve the efficacy and precision of physical education evaluations. This is essential for developing teaching techniques, refining educational methodologies, and eventually improving the learning experiences of students. Due to the complexity of evaluating various instructional consequences, such as skill acquisition and student engagement, a comprehensive system that can manage numerous data variables and interpret them effectively is needed.

Novel Method. An enhanced evaluation model based on the Genetic Algorithm-Back Propagation Neural Network (GA-BPNN) was created in order to overcome these issues. In order to evaluate and synthesize complicated data from a variety of physical education activities, this model makes use of deep learning capabilities. By including GA-BPNN, the model is able to continually adapt and optimize its assessment parameters, which enhances its capacity to forecast and evaluate the efficacy of instruction.

The rest of our research article is written as follows: Section 2 discusses the related work on various Physical Education and Deep Learning Algorithms. Section 3 shows the algorithm process and general working methodology of proposed work. Section 4 evaluates the implementation and results of the proposed method. Section 5 concludes the work and discusses the result evaluation.

2. Related Works. Students participating in sports inquiry learning should possess the awareness of conducting independent research, the capacity for independent thought, and an optimistic outlook on teaching. Teachers must support their students, foster an enjoyable learning atmosphere, and select effective teaching methods. The fundamental, useful, thorough, and complete aspects of the physical education curriculum are highlighted by the fundamental excellence in the sport. Physical education instructors must plan their lessons using the following four guiding principles: sports ethics and farming, sporting passion and ability, good habits and conduct, and sports excellence and will [10, 14]. Clear requirements correlate to each core competency, and courses that support those needs are available [13]. There is a blend of innovative and conventional information in the physical education core high-quality curriculum.

At present, one type of technology that is frequently employed is artificial intelligence (AI). The potential for its growth is rather large. Like how the use of electrical systems, the World Wide Web, and the use of steam engines has altered human existence and manufacturing, the way it looked has had a significant impact [2]. It has infused new vitality and given every walk of life new development prospects and orientations. The goal of machine learning (ML) technology is to investigate how to simulate or simulate animal behaviour learning on a machine. Its goals are to improve program performance, rearrange the current data structure, and learn new knowledge or skills. From a statistical point of view, machine learning is applied by forecasting the distribution of data and building an algorithm from the information at hand. Next, the model is used to forecast fresh data [15].

The instructional method of college physical education has rapidly changed from traditional collective instruction to personalized digital instruction. Students' engagement in the classroom has increased significantly, and the computerization of university physical education instruction has enhanced more in terms of science and precision [3]. College physical schooling classroom instruction has become more precise, adaptable, and vibrant. Simultaneously, there was a swift implementation of big data technology in college sports education management. The information pairs enable the implementation of smart teaching in a way that is more accurate, reliable, and scientific to support student learning and progress as well as college sports instruction [17].

Building a scientific, methodical, and acceptable assessment index system is the first step towards improving the teaching effect of physical education and aligning it with the overall purpose of the instructional effect assessment paradigm. The physical education theory course upholds the notion of helping the profession by combining professional qualities, organizing courses in a scientific manner, standardizing the curriculum and instructional materials, and making sure that professional theory classes, schedules for classes, and credit requirements are met to develop a pool of physical educators [16, 4, 8]. The teaching of exercise is the focus of the assessment index. It is important to pay consideration to the teaching environment and preparations in addition to the procedure of instruction and effect [11].

The research questions are:

1. How can deep learning models like the Genetic Algorithm-Back Propagation Neural Network (GA-BPNN) enhance the accuracy of physical education teaching outcome assessments compared to traditional methods?
2. What are the key factors contributing to assessment ambiguity in physical education, and how can these be systematically addressed through a deep learning approach?
3. How does the implementation of a hierarchical structure within the GA-BPBN model impact the evaluation of different instructional elements in physical education such as teaching behaviour, instructional material, and learning impacts?

3. Proposed Methodology. The proposed methodology for physical education learning is created using the Genetic Algorithm-Back Propagation Neural Network (GA-BPNN) method. Initially the data is collected from the student feedback, peer reviews and self-assessment reports. Next the data is pre-processed and then the physical education teaching is trained by using GA-BPNN method.

3.1. Teaching Physical Education System. The fundamental assurance for the school to promote scientific management, form school operating features, and cultivate high-quality talent for the nation is to use the concept of a scientific system to strengthen the building of a teaching management structure and create an integrated and stable teaching order. It is only through upholding a high standard of self-reflection and rational consciousness that educators may more effectively adjust to the fresh instructional format. The PE classroom is a crucial setting for teachers to engage in self-reflection.

Teaching physical education is a crucial component of education, and each component is put together in accordance with specific rules and guidelines that may both ensure and raise the standard of professional instruction. It also makes it obvious that the additional features of management of organizations, developmental assistance, supervision and measurements, and other components are part of the physical education major's teaching quality assurance system. The PE procedure One useful method for demonstrating instructors' beliefs is through their reflections. A peaceful and cooperative school atmosphere should be completely provided for teachers, and professional dialogue, interaction, exchange, and communication between instructors should be encouraged. It is possible to lessen teachers' solitary behavior and effectively promote their professional development by encouraging collaboration and support among teachers. Complex and multi-level topics are involved in the creation of training goals, training programs, profession organizing, curriculum, and textbook selection for physical education professionals.

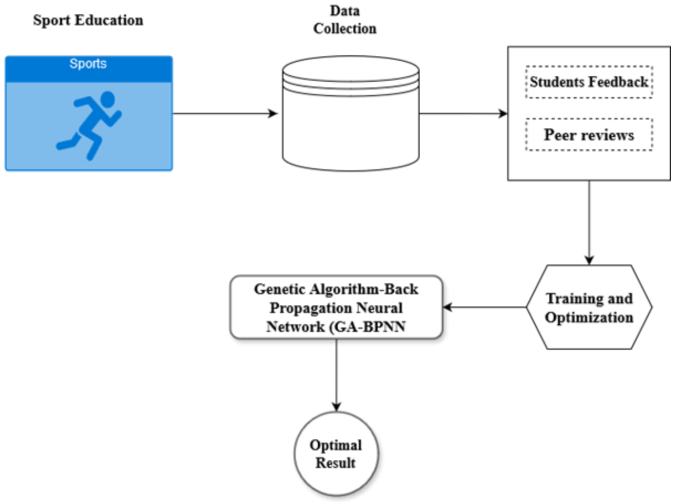

Fig. 3.1: Architecture of Proposed Method

3.2. Genetic Algorithm. A search heuristic known as a Genetic Algorithm (GA) was developed in response to Charles Darwin's notion of natural evolution. It reflects the process of natural selection, in which the most fit individuals are chosen to procreate and give rise to the subsequent generations of humans. The goal of using a genetic algorithm to optimize the method of assessment for the Assessment Model of Physical Education Teaching Effectiveness is to identify and select the best teaching techniques and achievements.

Encoding. Every potential solution, or individual, is depicted as a chromosome made up of many genes. Each gene might stand in for a performance-influencing factor in the assessment of education, such as student engagement, tactical knowledge, skill competency, etc.

$$Chromosomes = (gene_1, gene_2, \ldots\ldots, gene_n) \tag{3.1}$$

Every gene is represented by a series of binary codes or a numerical value that denotes various levels or states of the related educational component. The entire chromosome offers a thorough genetic picture of the efficacy of a teaching method or session. In this sense, a chromosome is made up of multiple genes, each of which stands for a certain dimension or feature that affects how educational assessments turn out. These elements might include anything from instructional strategies and skill competency to student involvement and tactical knowledge. For the genetic algorithm to successfully carry out tasks like crossover, mutation, and selection, the genetic representation is essential.

Initialization. First, a population of these chromosomes is created at random. A distinct collection of criteria related to teaching performance is represented by each chromosome.

$$Pop = \{Chromosome_1, Chromosome_2, \ldots\ldots, Chromosome_n\} \tag{3.2}$$

Fitness Function. A fitness function is applied to each chromosome in the population. The accuracy of the instruction that the chromosome encodes is measured by this function. One such model to serve as the basis for the fitness function is:

$$Fitness = (Chromosome_i) = f(gene_1, gene_2, \ldots\ldots, gene_n) \tag{3.3}$$

Selection. Analysing the fitness scores of the parent chromosomes, choose which ones to breed. The likelihood of being chosen increases with fitness level. There are several ways to accomplish this, including choosing a roulette wheel, choosing a tournament,

$$Sel = Selection(Population) \tag{3.4}$$

Crossover. When two parents' genetic information is combined, new offspring (solutions) are produced. While there are other approaches to crossover, the single-point crossover is a popular technique:

$$Child_1, Child_2 = Crossover(Parent_1, Parent_2) \tag{3.5}$$

Mutation. By introducing random gene changes, you can introduce variances in the progeny. This is necessary to keep the population's genetic variety intact and to enable the algorithm to investigate many possible solutions.

$$Mutated\_Child = Mutation(Child) \tag{3.6}$$

Replacement. Choose the most suitable people from both the present population and the new children to create a new population. This could be a straightforward swap out or involve more complex tactics like elitism.

$$Population_{new} = Replacement(Ppopulation, Offspring) \tag{3.7}$$

The phases 3 through 7 of the GA process must be repeated iteratively in order to develop the solutions and get the highest fitness score. This would, in the context of assessing the effectiveness of physical education instruction, correlate to the most effective teaching strategies as determined by the fitness function. Since the fitness function directs the evolutionary process, it is essential to describe it precisely when using GA to the evaluation model of physical education teaching performance. A variety of qualitative and quantitative criteria, sometimes set by pedagogical objectives or educational standards, may be considered by the fitness function.

3.3. Back Propagation Neural Network (BPNN). BPNN is a multilayer feedforward neural network that is trained via backpropagation, a supervised learning technique. An input layer, one or more hidden layers, and an output layer make up the network.

Input Layer. Features like as student engagement, skill development, participation rates, and adherence to curricular requirements are examples of quantitative metrics that are received by this layer in the context of physical education teaching performance.

Hidden Layers. These layers apply non-linear transformations after weighted sums are applied to the inputs. The performance of the network can be impacted by design characteristics such as the number of hidden layers and neurons in each layer. During training, these layers' weights and biases are changed.

Output Layer. The categorization or prediction is output by the last layer. This could take the shape of a performance score or categorical rating in an assessment model for teaching effectiveness.

Each neuron in the network processes the information before sending it to the layer above. The procedure keeps going till the output layer generates a preliminary forecast. By contrasting the goal values with the network's forecast, a loss function determines the error. Often used loss functions for classification tasks are cross-entropy and Mean Squared Error (MSE) for regression analysis. After that, the mistake spreads backward throughout the network, from the input layer to the hidden levels and back to the output layer. To compute the slope of the loss function in relation to the weights, backpropagation is utilized. The weights and biases are modified in an order that minimizes the error using optimization algorithms such as Stochastic Gradient Descent (SGD).

4. Result Analysis. The training of the suggested GA-BPNN method is examined in this section both before to and following optimization. The Scenario-Based Proposed GA-BPNN Learning Data collection is the source of the dataset used in the study. Throughout the test, a pair of scenarios are built up, one for the algorithm that is suggested during optimization and one for it after. After that, six loss scenarios for each of the two algorithms—0.001, 0.002, 0.003, 0.004, 0.005, and 0.006)—are obtained by altering the method's learning rate. Furthermore, the algorithm's optimization variables (the Adam optimizer and the Sigmoid function, respectively) and loss function are continuous.

The enhanced method's training procedure reveals that, while the loss curves at 4550 and 6800 have little peaks, the general inaccuracy of the network loss function has a decreasing trend and tends to be flat once the number of repetitions exceeds 3500. The system's loss function error is essentially steady below 0.2 after 8000 repetitions, and it continues to become stable over time. Learning with the initial approach demonstrates

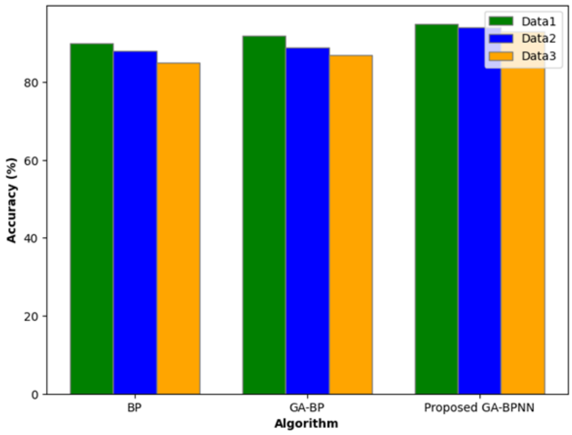

Fig. 4.1: Evaluation of Simple Data Accuracy

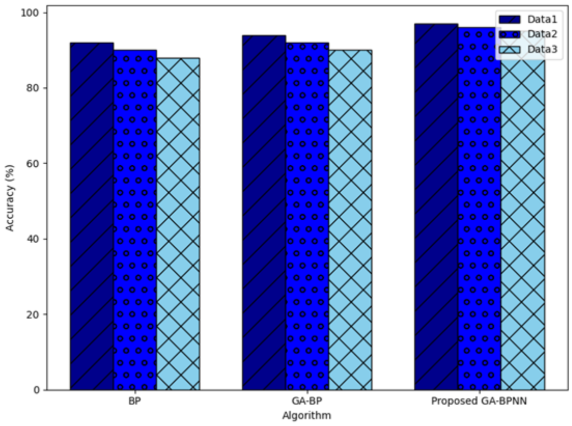

Fig. 4.2: Evaluation of Complex Data Accuracy

that the system's loss function error is constant at 7800 iterations, or less than 0.25. The training effect of the upgraded network model is better than that of the initial network approach, and the training error of the unchanged network is always larger than that of the enhanced network.

Three datasets, denoted as Data1, Data2, and Data3, exist. These could stand for various data kinds or data obtained from various sources. Accuracy is shown as a percentage on the vertical axis, which goes from 0% to 100%. Every algorithm is tested on every dataset, yielding a total of nine accuracy metrics. In figure 3.1 shows the result of simple data accuracy.

The three datasets show that the BP algorithm performs consistently, with about the same accuracy in each case. The datasets exhibit a little variance in the accuracy of the GA-BP method, with Data3 exhibiting the best accuracy. While Data1 and Data2 appear to perform similarly for the suggested GA-BPNN algorithm, Data3 exhibits a discernible improvement in accuracy.

On Data1 and Data2, the three methods all perform similarly. The accuracy of the BP algorithm on Data 3 seems to be marginally worse than that of GA-BP and the proposed GA-BPNN. On each of the three datasets, GA-BP and Proposed GA-BPNN perform comparably.

This displays the test time (green bars) and training time (red bars with diagonal hatching). GA takes the longest to train but the shortest to test. GA-BP requires more training time than Proposed GA-BPNN,

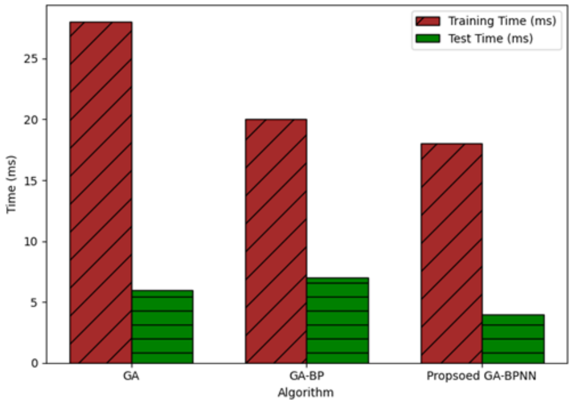

Fig. 4.3: Training and Testing Time of Data 1

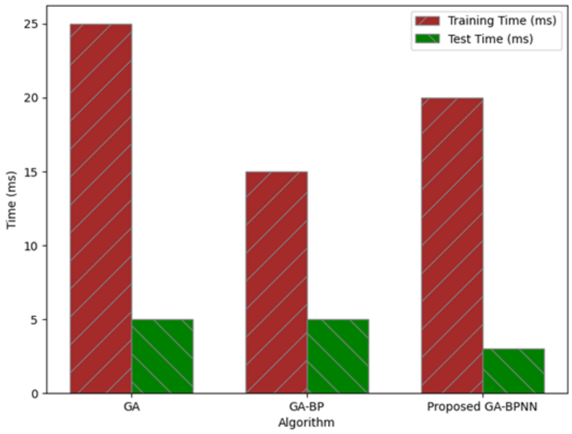

Fig. 4.4: Training and Testing Time of Data 2

but less than GA. The suggested GA-BPNN has a reasonable test time and the shortest training period. In figure 4.3 shows the training and testing time of data1.

It is comparable to the previous but a little less visually striking because it lacks the hatching patterns. The patterns show that for every algorithm, the test times are far less than the training periods. The initial image and the trends in training and test times for each algorithm continue to be the same. In figure 4.5 shows the training and testing time of data 2.

Employs a distinct hatching pattern for training times and a different color palette. The graphic pattern is in line with the earlier charts, which indicate that Proposed GA-BPNN has the shortest training timeframes. All algorithms have consistently low-test times, suggesting that the algorithms can swiftly assess new data after being trained. In figure 4.5 shows the training and testing time of Data 3.

GA typically has the longest training times, indicating that despite its potential thoroughness, it requires a lot of computing power. GA-BP outperforms ordinary GA in terms of training time, most likely because of backpropagation's optimization. The training time is significantly improved by the proposed GA-BPNN, suggesting either an optimized network architecture or a more effective training procedure. As testing a pre-trained model is substantially less expensive than training it, test times are typically substantially shorter than training periods for all algorithms. From GA to Suggested GA-BPNN, there is a discernible visual trend illustrating how these algorithms have evolved to become more time-efficient.

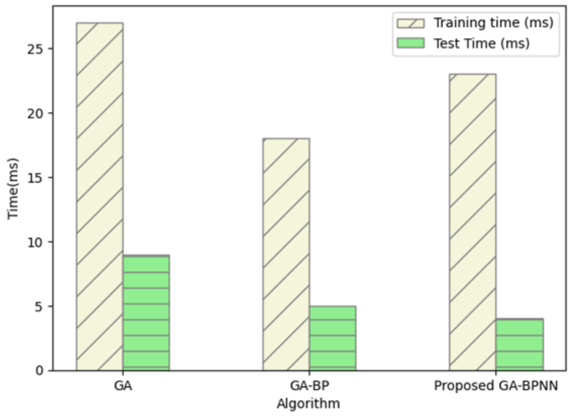

Fig. 4.5: Training and Testing Time of Data 3

5. Conclusion. Assessment ambiguity and its several manifestations in physical education teaching have an impact on the qualitative and quantitative evaluation results of instructional effects. High complexity and poor accuracy in the assessment of physical education teaching outcomes are addressed by a deep learning-based evaluation approach for physical education teaching and training excellence. The building of the assessment index system is based on learning impacts that affect the quality of education, as well as instructional materials, teaching behaviors, instructional resources, and teaching strategies. The Genetic Algorithm-Back Propagation Neural Network (GA-BPNN) was used to develop the model for assessing the learning impact of physical education in order to improve the assessment's accuracy. The cornerstone of the assessment approach is the observation of the entire instructional process. The broad objectives and a selected set of three-level indicators were reviewed in light of the various physical education teaching variables and the degree of uncertainty in the assessment. The (GA-BPNN) approach was used to develop the hierarchical structure and to generate the comprehensive score and overall rating of the hierarchy. The test findings indicate that the Accuracy of the teaching assessment model created in this study is higher than the industry average, indicating support for raising the standard of education.

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