

Cultural Perspectives on Basketball Artificial Intelligence Assistant Referee Mode: A Research Approach with Associative Memory Neural Network

Xiaofei Wang^{1*}

¹ College of Physical Education, Northwest Minzu University, Lanzhou, Gansu, 730000, China

Corresponding Author: Xiaofei Wang, <u>y210730253@stu.xbmu.edu.cn</u>

Abstract. The game of basketball is characterized by intense competition between the members of each team. It tests the athletes' physical fitness and the officials' ability to respond quickly under pressure and make split-second decisions. In addition, this capability needs to be improved by engaging in consistent practice. An intelligent training method that can realize automated feedback adjustment of faults is called an Associative Memory Neural Network(AMNN). By incorporating it into basketball training tactics, it is possible to have referees respond to different scenarios more quickly, which can help decision-makers enhance their degree of decision-making. Suppose this solution is transplanted to the intelligent training of artificial intelligence robots. In that case, the robot can accelerate the environment's real-time information collection and processing efficiency. This will allow the robot to capture various foul targets more quickly and make accurate decisions regarding the players on the field. A prompt reaction can raise the overall level of intelligent selection. To establish whether or not this plan is practicable, we employ an AMNN to instruct an artificial intelligence assistant referee robot for basketball games. According to the findings, the AMNN method has a quicker response speed and a lower error rate than the other three algorithms, which satisfies the requirements for developing an intelligent, high-precision picking robot.

Keywords: basketball game; AMNN; artificial intelligence; auxiliary referee; Cultural Perspectives **DOI:** https://doi.org/10.14733/cadaps.2024.S20.220-231

1 INTRODUCTION

Basketball is one of the most popular sports activities in the world [13],[26],[15], and 11% of the world's population participates in the sport. The International Basketball Federation, which serves as the governing body of basketball globally, has grown to include 212 member countries and 450 million registered players. Basketball is often considered the most popular team sport in the United States [18],[7]. The United States of America has long been regarded as the most potent force in basketball. Nevertheless, the rest of the globe is quickly closing the gap between them. If child and youth development programs continue to expand, then equality at the highest levels of the sport

will become a possibility. One of the most popular sports is basketball[24],[19]. It enjoys a significant global following as one of the three most essential balls in the world. Basketball can improve an individual's overall physical fitness and foster an individual's sense of competition and movement. Kind of movement. Basketball is a sport that may also be considered a way of life. The basketball reform has entered a more substantive stage by implementing the three primary initiatives for the regeneration and development of the ball. Basketball has a set of rules that guide the game, but the interpretation of these rules can vary across cultures. Different regions or countries may have their unique interpretations or preferences when it comes to enforcing rules. Cultural perspectives play a role in determining a foul, a violation, or an acceptable playing style. The introduction of AI assistant referee mode needs to consider these cultural variations to ensure fairness and consistency.

Nevertheless, the training progression of referees, one of the three primary themes of basketball games, is moving at a very moderate pace [17],[1]. This is in contrast to the booming basketball game. On the basketball court, players are frequently subjected to unjust treatment, including unfair competition, misuse of game authority, and physical violations of other players. As the viewing experience of basketball games improves and the sport becomes more professional, there will be two or more referees on the court simultaneously to officiate the game professionally. The presence of multiple referees decreases the likelihood of unfair occurrences and increases the level of quarantees significantly. It provides a dependable guarantee that the event will go in a fair and just manner while also ensuring that it will proceed smoothly. However, basketball referees face several significant challenges, including a low comprehensive ability level, a small number of imbalanced male-to-female officials, and a bad learning environment. Because these widespread issues do not correspond to the level of basketball development that is now taking place, they will pose a significant barrier to the expansion of basketball on the campus. Within the scope of this discussion, the growth law of school basketball and the psychological and physiological well-being of kids are adhered to by this study. By delving into the intricate interplay between technology and culture, this study aims to provide valuable insights into the acceptance, challenges, and potential adaptations required for an AI assistant referee to align seamlessly with the diverse cultural expectations surrounding basketball. As we embark on this exploration, it is with the recognition that the future of sports technology should be cutting-edge, culturally sensitive, and inclusive.

Competition fairness [25[],[4],[6] is the fundamental value demanded by current basketball sports competition. Fairness is the cornerstone of the most important values of modern society. Fairness is the cornerstone of the essential values of contemporary culture. Academic circles and the industry have always been hard at work trying to figure out how to improve justice inside sporting events and within social operations. The general opinion among members of society, especially in light of the proliferation of information technology, is that the quality of fair realization and the operational efficiency of businesses should be improved using technology. It is necessary to reconsider the dual effects of technology development on human beings and human society within the context of human nature and the ethical scope of human legislation to be better able to deal with the risks and challenges posed by the intervention of technology in social life. This is necessary to be able to better cope with the risks and challenges posed by the intervention of technology in social life. The need for fair play in basketball contests, combined with the advancements made in information technology, has resulted in the widespread usage of assistive technology for referees. How do we get a handle on the complicated link between the involvement of technology and the achievement of fair competition? After current sports have entered the stage of information civilization, the Institute of Basketball Sports Philosophy will need to respond to this essential theoretical question[22], [28]. Basketball referee aid technology is a technical way to assist referees in making proper choices. This is accomplished by employing particular strategies, methods, and tools in the referee's officiating process, which amplifies, reproduces, and reconstructs the game process. The referee uses technical means to improve both the quality of the penalty and the referee's fairness by employing auxiliary measures. This is done to ensure that both the process of the basketball tournament and the results are fair. Existing technologies, methodologies, tools, and newly developed or upgraded technologies are typically utilized when applying referee-helping technology to assist referee activities. Currently, the primary emphasis is placed on using analog image technology and digital computer technology, in conjunction with the dissemination characteristics of contemporary information technology, to actualize the amplifying, reproducing, and reconstructing of the game process. The act of refereeing is a procedure in which the referee determines the only correct refereeing result based on the game's situation through fact-finding and the application of rules from ongoing cases. This is done to ensure that the game is played moderately. The pending cases are a fact that cannot be changed and have no value attached to them. Following the completion of the adjudication procedure, the adjudication outcome with the value attribute is determined. According to the research that has been done on referee philosophy, for the work of refereeing to be successful, it requires the joint support of the referee's ontological authority and epistemological privilege. This is so that factual judgment and value judgment may be completed. The execution process of the referee consists of elevating accurate data to the level of value judgments.

Because the AMNN [5],[20],[16] not only has solid functions for self-learning, associative storage, and high-speed optimization but also has good functions for security, it has good performance. As a consequence of this, people have presented an artificial intelligence-assisted referee based on an AMNN. Additionally, some algorithm implementation and analysis are provided. A systematic training program for professional basketball referees is investigated here by examining the existing state of officiating at the sport's highest level. We discovered an algorithm for an AMNN by utilizing artificial intelligence methodology. Additionally, we contributed to the growth and development of basketball by instructing an auxiliary referee robot.

2 RELATED WORK

In this information age, not only has the volume of information expanded rapidly, but how it is processed has also become more sophisticated. The processing of information, previously done manually, has been largely replaced by computer processing thanks to advances in information technology, which are represented by artificial intelligence. Research in the field of computer science has a significant emphasis on artificial intelligence [12],[2],[9]. Machines now have the same transaction processing skills as human brains, thanks to advancements in algorithm fusion and the design of computer programs. As a result, machines can do some complicated activities instead of humans. The magnitude of basketball game databases has significantly expanded in recent years due to the widespread implementation of information from large amounts of data and then using that information to optimize a game. The development of artificial intelligence technology has led to a better solution for this problem. The processing and classification of basketball game field data are substantial uses of artificial intelligence technology. This technology can then delve deeper into the data to unearth the underlying laws concealed beneath the game data and private coaches with basketball games. The scientific foundation upon which tactical decisions are made on the ground.

For their groundbreaking research on AMNNs [27],[21],[14], a few researchers used a straightforward single-layer fully connected neural network. Their goal was to recall statistical graphs that contained noise. Since then, AMNNs have been the subject of significant theoretical and practical study. Sure, researchers have developed a multi-dimensional AMNN, which has been used in visual recall. The visual recall effect was enhanced due to the contribution of a few researchers who utilized irregular convex polygons as vectors. However, when the image is affected by high noise levels greater than sixty percent, the image is said to be disturbed by k percent. This indicates that the image's gray value of k percent has been altered. When utilizing the procedures suggested by other academics, the speed of image recall could be faster, and the outcome could be better.

The Hopfield network is a linked network suggested by several academics as a potential candidate for use as an associative memory. The Hopfield network elucidates the connection between neural networks and dynamics, uses nonlinear dynamics to address the problem, and forms a new calculation approach by utilizing the concept of energy function. It is pointed out that the information is stored in the connections between neurons in the network, forming a Hopfield network, and the output of neurons only takes 1 and 0, so it is also called a binary neural network. The characteristics of this type of neural network are studied, and the stability criterion of the neural network is established. It is a Hopfield neural network with discrete connections. Some researchers design and develop a feedback neural network realized by analog electronic circuits. They observe that operational amplifiers can recognize neurons, and electronic circuits can simulate the connection of all neurons. This type of neural network is known as a continuous Hopfield neural network. They are all straightforward examples of artificial neural networks, each with a single connection layer. The discrete and continuous models can be used for associative memory and optimization computation. However, the discrete model is more commonly used. The AMNN functions well in many respects, and we can apply it to the study of the development of an artificial intelligence auxiliary referee for basketball.

Participants' initial desires to enhance the fairness of the competition were the critical impetus for the development of referee-assisted technology [3], [23]. This demand has been the primary driving force behind the rise of this technology. When various interests are involved in the activities around a high-level competition, those interests become intricately connected to the outcomes of the competition. When interests are concerned, players significantly increase the number of demands for an equitable competition. The solution to the problematic logical problem that is the creation of fair competition lies in the system. The idea of fairness and the methods by which it can be realized both limit the possibility of having fair competition. Therefore, in response to the public's expectation that there would be improvements to the fairness of competition, the first thing that has to be done is to answer the question of how competition fairness will be realized from the principle level. Any attempt to make the competition more fair must begin with the component that creates the factual basis. This is the area in which referee assistant technology can make up for the deficiencies of manual refereeing. The 100-meter race in the early days of the modern Olympic Games was timed by manual mechanical equipment. The error rate of manual timing needed to be lowered, and it was challenging even to record the race ranking. The Micrographe timer and the McBridge timing system were experimentally implemented to confirm the athletes' placement in the competition [8]. This was done since there was an excessive amount of disagreement. Later, the Raced Omega Timer and the Scan-O-Vision systems were utilized to increase the timing accuracy to 0.01, significantly resolving the issue of measuring the competition's final results. Restoring the facts is simply the first step in achieving the fairness of the competition, and it only plays an indirect role in promoting. However, from the point of view of the referee process, the assistance of referee technology can improve the competition's fairness. Since the rules themselves cannot be altered, the only way for non-law enforcement groups to satisfy their desire for fair competition is for the competition to make use of referees who are equipped with assistive technology.

Referees in basketball are required to make decisions in a matter of milliseconds [10]. As a result, they need to be well-prepared to deal with any situation that may arise and achieve adequate performance during the game to make them more capable of performing court functions. The making of decisions and the performance of referees are both impacted by various factors, including the instruments that make it feasible to measure those factors. In light of this scientific landscape, it is vital to collect diverse studies to conduct a more in-depth investigation of the performance of basketball referees. As a result, the competition's decision-making requirements regarding physiology, psychology, and the knowledge already available regarding basketball referees' performance are studied. To devise an effective training regimen that caters to the requirements of both the referee and the game, we need your help.

3 RESEARCH DESIGN

3.1 Data Sources

Our findings stem from observations made at a collegiate basketball match in Beijing. The information in the database is mainly made up of different tables, such as the primary information table, the game information table, the script information table, and so on. In the script transaction database, the appropriate technical action attribute column assignments for action scripts that exist and actions that do not appear are represented by the values 1 and 0, respectively. After several cycles, the database's script transaction table, also known as the transaction data table mined by association rules, can be constructed. It is difficult for typical data processing methods to successfully achieve data cleansing, conversion, mining, and other operations due to the vast amount of basketball game information stored in the database. Because of this, the big data technology used for the basketball game backdrop database will be based on the association's guidelines. Data mining is better. Manage and analyze the statistics gathered from the basketball games you play. The data set describes the most critical information in the script transaction table. Only a portion of the data is shown because the script transaction is of type int. The database of information about basketball games is displayed in Figure 1.



Figure 1: Basketball game information library.

The training set comprises 70 percent of the dataset, while the test set comprises 30 percent. The AMNN model is trained using the training set, and the performance of the fitted model is evaluated using the test set. Both sets are referred to here as assets.

3.2 AMN Building

The bidirectional AMNN (BAMNN) is frequently utilized in various associative memory networks. BAMNN can achieve bidirectional hetero-association, in contrast to the auto-association that the Hopfield network is capable of. As can be seen in Figure 2, BAMNN is a two-layer network that operates in both directions. When one layer receives a signal at its input, the other can get an output. There is neither an explicit input nor an output layer. Instead, the initial input may act on any network layer, and information may be transmitted in any way despite the absence of such layers.

1.1.1 BAMNN Architecture

The progression of the network from a dynamic state to a steady state is known as BAMNN. When the memory vector X^p acts on the input layer of a BAMNN with a given weight matrix, the input layer produces the output $X(1) = X^p$ at time t = 1.



Figure 2: Topological structure of BAMNN.

This output is then transmitted to the output through the weight matrix W layer. The production of the output layer, $Y(1) = f_y[WX(1)]$ at time t = 1, is obtained following a nonlinear transformation by the activation function $f_y(\cdot)$ of the neuron on this side. The output is then transmitted from the output layer back to the input layer through the weighting matrix W^T as the input at the next moment. The output $X(2) = f_x[W^TY(1)] = f_x\{W^T[f_y(WX(1))]\}$ of this layer is obtained at the time t=2 after undergoing a nonlinear transformation utilizing the activation function $f_x(\cdot)$ of the neurons in the input layer. This process will continue until the states of all neurons are permanently fixed. At this point, the state of the network is referred to as the steady state, and the consequence of the bidirectional association of the memory vector X^p is the matching output layer output vector Y^p . In the other direction, if the memory vector Y^p is applied to the output layer, X^p can connect with the input layer.

4.2.1 BAMNN Parameter Description

BAMNN has n neurons in its input layer and m neurons in its output layer, for a combined total of N neurons, equal to n plus m. The weight matrix from the input layer to the output layer is denoted by the letter W. In contrast, the weight matrix from the output layer back to the input layer is represented by the letter W^T . Consider the hyperbolic tangent function, the neuron activation function, denoted by $f(\cdot) = \tanh(\cdot)$. X(t) is the network state vector that represents the input layer. The state vector of the network at the output layer is the letter Y (t). $x_i(t)$ and $y_i(t)$ are the components that make up the state vector. Describe the state that neuron I or j was in at the given time. The following definitions apply to both the state vector and its components:

$$X(t) = [x_1(t), x_2(t), \dots, x_n(t)]$$
(1)

$$Y(t) = [y_1(t), y_2(t), \dots, y_n(t)]$$
(2)

$$x_{i}(t+1) = tanh\{\frac{1}{2\alpha}[\sum_{j=1}^{m} W_{ji}y_{j}(t) - \beta_{i} + \lambda_{i}(t)]\}$$
(3)

$$y_i(t+1) = tanh\{\frac{1}{2\alpha} [\sum_{i=1}^n W_{ji}(x_j(t) + a_i(t)) - \beta_j + \lambda_j(t)]\}$$
(4)

Among these, α denotes the steepness parameter. W_{ij} is the synaptic weight from neuron i to neuron j. The activation threshold of neuron I is characterized by β_i . If the threshold is equal to zero, the energy function of the network will be denoted as $E = -X^T W^T Y$. $A_i(t)$ is the input sent to the input layer Signal, and $\lambda_i(t)$ is a Gaussian noise component with a mean of 0 and IID. The network is

equipped with M pairs of memory vectors $(X^{\eta}, Y^{\eta}), \eta = 1, 2, ..., M, x \in \{-1,1\}^n, y \in \{-1,1\}^m$. Each of these corresponds to a different M-ary signal.

$$(X^p)^T X^k = \begin{cases} 0, p \neq k \\ n, p \neq k \end{cases}$$
(5)

$$(Y^p)^T Y^k = \begin{cases} 0, p \neq k \\ m, p \neq k \end{cases}$$
(6)

Hebb's rule, often known as the outer product sum approach, is used in the construction of the weight matrix W that makes up the network:

$$W = \frac{1}{N} \sum_{\eta=1}^{M} Y^{\eta} (X^{\eta})^{T}$$
⁽⁷⁾

A decision rule is designed at the end that will be receiving the information, and the overlap m_{η} between the state vector Y(t) and the memory vector Y^{η} at the output end of the network is described as follows:

$$m_{\eta}(t) = \frac{1}{m} Y(t)^{T} Y^{\eta}$$
(8)

The m-dimensional space V of the state vector Y(t) can be divided into M subsets using the overlap $m_{\eta}(t)$. One of these subsets, $V_{\eta} = \{Y | m_{\eta}(t) \ge m_{j}(t)\}$, represents the attraction domain that corresponds to the memory vector Y^{η} . When the modulation vector AX^{η} is fed into the network, the network state vector Y(t) will, in a statistical sense, primarily lie inside the attraction cap V sub eta domain. This is because the modulation vector AX^{η} is being fed into the network. After that, to decode the M-ary digits at the sampling time $t = jT_b$, one must first determine which of the subsets V_{η} the network state vector Y(t) belongs to. This is the same as calculating the overlap amount that has to be decoded for $m_{\eta}(jT_b)$, and if $Y(t) \in V_{\eta}$ is present, interpreting it as a symbol that corresponds to $m_{\eta}(jT_b)$. Calculating the error probability P_e , which is defined as follows, this study measures the decoding performance of system transmission of the decision rules described above:

$$P_{e} = \sum_{i=1}^{M} p(i) [\sum_{j=1, j \neq i}^{M} p(j|i)]$$
(9)

Among them, p(i) is representative of the prior probability of the number I in the M-ary signal. This prior probability is generated from the experimental signal set using statistics, utilizing the multivariate signal set with equal prior probability. p(j|i) indicates when the input was received. When the number is assigned to i, the probability of decoding to j can be determined by contrasting the outcome of the system's decoding operation with the initial set of input signals and tallying the number of incorrect symbols.

As seen in the table below, the accuracy rate serves as the evaluation index for the model.

$$Acc = \frac{TP}{TP + FN + FP + TN}$$
(10)

4 RESULTS

While we apply the other three algorithms to this dataset, we refer to the BAMNN approach as our algorithm. We evaluate the performance of the OUR algorithm in comparison to the convolutional neural network algorithm (CNN), the multilayer perceptron algorithm (MLP), and the random forest method (RF). A comprehensive and multi-level analysis of the four algorithms is carried out here.



Figure 3: Accuracy as a function of the number of iterations.

Figure 3 depicts how the accuracy of the OUR method, the CNN algorithm, the MLP algorithm, and the RF algorithm changed as the number of iterations increased. These algorithms were used to train a neural network. It is clear from the chart that the number of times the OUR algorithm is iterated contributes positively to the accuracy of the results it produces. The accuracy of the OUR algorithm is the highest among the four algorithms right at the start of the iteration. In addition to this, we can see that during the entirety of the iterative process, the accuracy of our method is the highest among the other three algorithms. The accuracy of the CNN algorithm is ranked second in the early iterations, but it experiences a little decline in the middle iterations of the process. However, the precision of the CNN algorithm was only one of the critical factors in the final result. The accuracy of the MLP and RF algorithms gradually improves when the number of iterations performed increases. During iteration, the accuracy of these two algorithms steadily improves alternatingly. The final findings demonstrate that, among the four algorithms tested, the accuracy of the OUR algorithm is the highest.

The four different algorithms' loss values are shown in Figure 4, along with their progression when the number of repetitions increases. It is clear that as the number of iterations increases, the loss caused by each of the four methods will become less severe. The OUR algorithm suffers the most minor damage at the early moment, followed by the CNN algorithm, the RF algorithm, and the MLP algorithm in that order. The MLP algorithm suffers the most damage. As more iterations of the complete model are performed, a lower percentage of the four algorithms are finally lost, and this trend continues until it is stabilized. The ultimate loss reveals that the OUR algorithm suffered the slightest loss overall, followed by the CNN algorithm in second place, the RF algorithm in third place, and the MLP algorithm suffering the most significant loss overall. This demonstrates that out of the four algorithms, the one with the minimum loss value in the function that measures loss is the OUR method. This indicates that the model of the OUR algorithm is more applicable to this dataset in terms of its practicality.

A comparison of the recall and precision rates achieved by each of the four algorithms is presented in Figure 5. As mentioned in the previous paragraph, the recall rate of the OUR algorithm is the highest, followed by the recall rate of the CNN algorithm, the recall rate of the RF algorithm, and the recall rate of the MLP algorithm, which is the lowest. The following subgraph demonstrates that the recall rate of the OUR algorithm is the highest, followed by the recall rate of the CNN algorithm, followed by the recall rate of the MLP algorithm and finally followed by the recall rate of the RF algorithm, which is the lowest.



Figure 4: Loss values under different models.



Figure 5: The recall and precision of the four algorithms.

From the comparison of the recall rate and the precision rate, it can be seen that the OUR algorithm is the best among the four algorithms in these two indicators. This conclusion can be drawn from the fact that the OUR algorithm was chosen as the focus of this discussion. This demonstrates that the functionality of the OUR algorithm is at its highest possible level.

The chart illustrating a comparison of the F-scores of the four algorithms can be seen in Figure 6. As a result, we can deduce that the F-score of our algorithm is greater than that of CNN's algorithm, MLP's algorithm, and RF's algorithm, respectively. This is the case because our algorithm was developed first.

5 CONCLUSION

The AMNN basketball artificial intelligence assistant referee system proposed in this study is a practical move that may adapt to the betterment of the contemporary economic level and the development of science and technology. In today's society, participation in sports and athletic competitions is prevalent. On the one hand, the artificial intelligence referee assistance system helps basketball players promptly. It compensates for the shortcomings of referees and athletes who need help to make response plans in response to the increasing number of basketball competitions and the shortening of the competition cycle. The referee is responsible for adjusting the current level of fouls and making both prompt and accurate decisions regarding fouls on the basketball floor.



Figure 6: F-score of the four algorithms.

On the other hand, the system is based on the game's massive data, takes very little time to make a foul judgment that is more reasonable, and offers a more accurate choice and penalty plan reference in the process of negotiating the race against time. This approach has positively contributed to the basketball players' competitive level and the tactical layout strategy from the comprehensiveness and efficiency of tactical creation points of view. Even though the system AMNN algorithm presented in this paper has achieved specific results in response efficiency and high satisfaction, it still needs to be improved regarding decision-making rationality and victory rate. This is because, at the moment, the system has achieved specific results in response efficiency and high satisfaction. In our ongoing research, we need to concentrate on improving how decisions are made. Regarding strategic decision-making in basketball, the degree of artificial intelligence referee aid systems is constantly improved thanks to the efficiency of algorithm mining data features.

The AMNN that is proposed in this paper has the potential to effectively assist the referee on the spot in making more accurate judgments. This would further improve the fairness of the basketball game, assist the referee in playing the game more effectively, and make the already excellent game of basketball even better. Offered to more people as a presentation. This plays a part in fostering the growth of basketball in our nation and is necessary for its continued success.

Xiaofei Wang, https://orcid.org/0000-0002-4571-3050

REFERENCES

- [1] Appelt, D. E.: Introduction to Information Extraction, Ai Communications, 12(3), 1999, 161-172. <u>https://doi.org/10.1016/S0030-4018(99)00572-6</u>
- [2] Bannerjee, G.; Sarkar, U.; Das, S.: et al. Artificial Intelligence in Agriculture: A Literature Survey, International Journal of Scientific Research in Computer Science Applications and Management Studies, 7(3), 2018, 1-6.
- [3] Barry, J.; Barry, J.: Assistive Technology in Libraries for Patrons with Disabilities: An Annotated Bibliography, Retrieved January 20, 2012, 2019.
- [4] Benhamou, F.: Fair Use and Fair Competition for Digitized Cultural Goods: the Case of eBooks, Journal of Cultural Economics, 39(2), 2015, 123-131. <u>https://doi.org/10.1007/s10824-015-9241-x</u>

- [5] Carpenter, G. A.: Neural Network Models for Pattern Recognition and Associative Memory, Neural Networks, 2(4), 1989, 243-257. <u>https://doi.org/10.1016/0893-6080(89)90035-X</u>
- [6] Catlin, D. H.; Murray, T. H.: Performance-Enhancing Drugs, Fair Competition, and Olympic Sport, Jama, 276(3), 1996, 231-237. <u>https://doi.org/10.1001/jama.276.3.231</u>
- [7] COHEN, A. R. I. R.; METZL, J. D.: Sports-Specific Concerns in the Young Athlete: Basketball, Pediatric Emergency Care, 16(6), 2000, 462-468. <u>https://doi.org/10.1097/00006565-200012000-00023</u>
- [8] Fasth, J. E.; Loberg, B.; Norden, H.: Preparation of Contamination-Free Tungsten Specimens for the Field-Ion Microscope, Journal of Scientific Instruments, 44(12), 1967, 1044. <u>https://doi.org/10.1088/0950-7671/44/12/428</u>
- [9] Frolov, D.; Radziewicz, W.; Saienko, V.: et al. Theoretical and Technological Aspects of Intelligent Systems: Problems of Artificial Intelligence, International Journal of Computer Science & Network Security, 21(5), 2021, 35-38.
- [10] García-Santos, D.; Gómez-Ruano, M. A.; Vaquera, A.: et al. Systematic Review of Basketball Referees' Performances, International Journal of Performance Analysis in Sport, 20(3), 2020, 495-533. <u>https://doi.org/10.1080/24748668.2020.1758437</u>
- [11] Jiang, W. J.; Qin, K. L.; Huang, B.: et al. Huanggang Middle School Basketball Teaching Present Situation and Countermeasure Research, Int. J. Huma. Soci. Scie. Edu, 3(6), 2016, 51-57. <u>https://doi.org/10.20431/2349-0381.0306009</u>
- [12] Kandlhofer, M.; Steinbauer, G.; Hirschmugl-Gaisch, S.: et al. Artificial Intelligence and Computer Science in Education: From kindergarten to University, //2016 IEEE Frontiers in Education Conference (FIE). IEEE, 2016, 1-9. <u>https://doi.org/10.1109/FIE.2016.7757570</u>
- [13] Li, B.; Xu, X.: Application of Artificial Intelligence in Basketball Sport, Journal of Education, Health and Sport, 11(7), 2021, 54-67. <u>https://doi.org/10.12775/JEHS.2021.11.07.005</u>
- [14] Liu, X.; Zeng, Z.; Wen, S.: Implementation of Memristive Neural Network with Full-Function Pavlov Associative Memory, IEEE Transactions on Circuits and Systems I: Regular Papers, 63(9), 2016, 1454-1463. <u>https://doi.org/10.1109/TCSI.2016.2570819</u>
- [15] Madarame, H.: Game-Related Statistics Which Discriminate Between Winning and Losing Teams in Asian and European Men's Basketball Championships, Asian Journal of Sports Medicine, 8(2), 2017. <u>https://doi.org/10.5812/asjsm.42727</u>
- [16] Morelli, L. G.; Abramson, G.; Kuperman, M. N.: Associative Memory on a Small-World Neural Network, The European Physical Journal B-Condensed Matter and Complex Systems, 38(3), 2004, 495-500. <u>https://doi.org/10.1140/epib/e2004-00144-7</u>
- [17] Nabli, M. A.; Ben, Abdelkrim N.; Fessi, M. S.: et al. Sport Science Applied to Basketball Refereeing: A Narrative Review, The Physician and Sportsmedicine, 47(4), 2019, 365-374. <u>https://doi.org/10.1080/00913847.2019.1599588</u>
- [18] Post, E. G.; Rosenthal, M. D.; Root, H. J.: et al. Sport Specialization Behaviors are Associated with History of Reported Injury in Youth Basketball, Journal of Pediatric Orthopaedics, 41(8), 2021, 507-513. <u>https://doi.org/10.1097/BPO.000000000001908</u>
- [19] Randazzo, C.; Nelson, N. G.; McKenzie, L. B.: Basketball-Related Injuries in School-Aged Children and Adolescents in 1997–2007, Pediatrics, 126(4), 2010, 727-733. <u>https://doi.org/10.1542/peds.2009-2497</u>
- [20] Specht, D. F.: Probabilistic Neural Networks for Classification, Mapping, or Associative Memory, //ICNN. 1988, 525-532. <u>https://doi.org/10.1109/ICNN.1988.23887</u>
- [21] Sun, J.; Han, G.; Zeng, Z.: et al. Memristor-Based Neural Network Circuit of Full-Function Pavlov Associative Memory with Time Delay and Variable Learning Rate, IEEE Transactions on Cybernetics, 50(7), 2019, 2935-2945. <u>https://doi.org/10.1109/TCYB.2019.2951520</u>
- [22] Szolga, L. A.; Szocs, J.: RFID Tracking System for the Basketball Game, //AIP Conference Proceedings. AIP Publishing LLC, 2570(1), 2022, 030007.<u>https://doi.org/10.1063/5.0099641</u>
- [23] Tinker, A.: Assistive Technology and its Role in Housing Policies for Older People, Quality in Ageing and Older Adults, 2003. <u>https://doi.org/10.1108/14717794200300008</u>

- [24] Trojan, T. H.; Cracco, A.; Hall, M. et al. Basketball Injuries: Caring for a Basketball Team, Current Sports Medicine Reports, 12(5), 2013, 321-328. https://doi.org/10.1097/01.CSMR.0000434055.36042.cd
- [25] Vagstad, S.: Promoting Fair Competition in Public Procurement, Journal of Public Economics, 58(2), 1995, 283-307. <u>https://doi.org/10.1016/0047-2727(94)01472-Z</u>
- [26] Wang, J.; Song, X.: Development Status and Influencing Factors of Competitive Basketball Management System Under the Background of Deep Learning, Computational Intelligence and Neuroscience, 2022, 2022. <u>https://doi.org/10.1155/2022/5659467</u>
- [27] Yang, J.; Wang, L.; Wang, Y.: et al. A Novel Memristive Hopfield Neural Network with Application in Associative Memory, Neurocomputing, 227, 2017, 142-148. https://doi.org/10.1016/j.neucom.2016.07.065
- [28] Žemgulys, J.; Raudonis, V.; Maskeliūnas, R.: et al. Recognition of Basketball Referee Signals from Videos using Histogram of Oriented Gradients (HOG) and Support Vector Machine (SVM), Procedia Computer Science, 130, 2018, 953-960. <u>https://doi.org/10.1016/j.procs.2018.04.095</u>

231