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USING GENETIC ALGORITHM TO OPTIMIZE THE TRAINING PLAN AND GAME STRATEGY OF BASKETBALL PLAYERS

QIU DAWEI*

Abstract. Basketball teams rely heavily on the effectiveness of their practice regimens and game plans to succeed. The intricacy of the game and the range of skills players must possess make it extremely difficult to develop effective training plans and tactical techniques. The use of genetic algorithms (GAs) as a cutting-edge technique to enhance basketball players' practice regimens and game strategies is investigated in this work. Inspired by biology and natural selection, genetic algorithms provide a potent optimization method that, via the repeated steps of evolution, can find close to ideal solutions to challenging issues. As chromosomes made up of genes relating to different parameters and tactics, prospective training plans and game tactics are represented by GAs, which enable them to efficiently search across the large solution space and find combinations that optimize desired results. As part of the research approach, the goals and limitations of the optimization issue are defined. Fitness functions are intended to assess each potential solution's efficacy, directing development toward better solutions across a series of iterations. This study shows how effective genetic algorithms are in optimizing basketball players' training regimens and game strategy through simulators and real-world tests. In order to continually enhance player growth and team competitiveness, coaches can use GAs to refine and modify tactics based on feedback as well as performance data in an iterative manner. The results of this study have significance for team sports other than basketball, where results are heavily influenced by the interaction of players' individual abilities, teamwork, and decisions about strategy. In the end, incorporating algorithms based on genetics into sports analytics presents a viable way to improve coaching techniques and reach the highest levels of efficiency in sporting settings.

Key words: genetic algorithm, optimization, game strategy, basketball players, deep learning

1. Introduction. The development of technology for computer vision has led to a growing emphasis on technological achievements, especially in sports [7]. Videos can be used for human action identification and behavioral analysis, but this equipment can also help officials make better decisions about sports motions and give players, trainers, or analysts insights into correct motion strategies. In actuality, the field of sports science research is booming these days, with the goal of tracking players, identifying them, and identifying the activity they execute. Therefore, increasing the total efficacy of athletic training requires making coaches' training plans more scientific in character and utilizing cutting-edge technologies like computer vision to analyse athletes' performances [8, 20, 2].

An essential part of teaching and fostering pupils' healthy development is basketball. Participating in basketball games can help children develop their strong will, unwavering spirit, camaraderie, and coordination skills in addition to their endurance [21]. Basketball instruction is still taught using the conventional method of having instructors explain concepts, provide examples, and have students mimic them mechanically. This approach necessitates a high degree of independence for students and interaction between teachers and pupils. The total impact and caliber of basketball instruction are significantly diminished by this full-house irrigation-based teaching strategy, which also stifles pupils' capacity for original thought and creativity [6]. This is the final goal of teaching physical education, and it is a crucial issue that educators must address. Basketball is a contemporary sporting event as well as a full exercise game.

Basketball instructors design customized training schedules for players to improve their abilities. In the past, coaches made training strategy decisions based on their own experiences as well as the athlete's technical proficiency [1]. Evaluating this approach's success is challenging because it heavily relies on personal bias and necessitates a thorough examination of motion. Efficiency and precision are essential components of training in modern sports. Teachers can greatly enhance training results if they can correctly determine an athlete's

*Department of Physical Education, Guangxi University of Traditional Chinese Medicine; Nanning, Guangxi; 530200; China (qiudaweispace1@hotmail.com)

sports posture [13]. Therefore, identifying sports postures precisely is essential to developing training regimens that make scientific sense and improving the performance of athletes. The combination of estimation of human poses and action recognition systems has been made possible by improvements in basketball sports, and this has a significant impact on raising the points scored rate [4].

Teams must constantly adapt and improve their practice plans and game plans to keep ahead of the intense demands of competitive basketball. Making efficient training plans and in-game strategies is difficult due to the intricacy of synchronizing the talents and tactics of several players. Conventional approaches might not be able to adequately convey the dynamic character of the game and the interaction between different tactical components. Innovative strategies that may methodically and effectively assess and enhance team performance are required in this circumstance. Inspired by biological evolution, genetic algorithms (GAs) provide a potent optimization tool that can search large solution spaces and find optimal techniques that traditional methods might miss. The potential for GAs to transform basketball strategy and training by adjusting to real-time performance

The main contribution of the proposed method is given below:

1. To ensure continuous progress and optimal performance, our system uses a genetic algorithm to customize training routines that adjust to the changing skill sets and fitness levels of basketball players.
2. We created a dynamic framework for game strategy that use evolutionary algorithms to construct intricate in-game strategies, optimizing plays by taking opponent data and real-time player statistics into account.
3. We present a thorough analysis of the differences between our GA-optimized technique and conventional training and strategy methods, highlighting the superior results in terms of player growth, team performance, and strategy adaptation.

Research helps to identify solutions for

- In comparison to conventional coaching techniques, how good are genetic algorithms in optimizing basketball training schedules and game strategies?
- What are the best parameters and strategies to reflect basketball training and strategy optimization that may be efficiently stored as genes within the chromosomes of genetic algorithms?
- In a genetic algorithm framework, what are the best fitness functions to assess basketball practice plans and tactics?

The rest of our research article is written as follows: Section 2 discusses the related work on various Basketball player, game strategy, sports teaching 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. Among the more popular sports in the globe is basketball. This societal impact also corresponds with a high level of academic documentation, as this is one of the sports with the most research output [10]. These studies focus on a variety of topics, including game indicators (GI), psychological factors, nutritional elements, tactics and techs, and physical fitness (PF) [14, 15, 5, 9]. Some research methods are used independently of one another, with no connection among the various subjects. Basketball is a complicated sport with many interacting variables; hence the progress of basketball study involves multidisciplinary studies including numerous objects of study. By examining any potential connections among physical fitness and game indicators, this study seeks to determine the relationship between the two of them.

Furthermore, GI may be impacted by several ambient factors. In accordance with the classification [22], three categories of matches—equal, unbalanced, and extremely imbalanced—were specified in this line based on the outcomes. Based on this categorization and the analysis [11] concluded that whereas two-point shooting determines the outcome of lopsided games, the quantity of rebounds determines even games. Furthermore, the researcher [18] verified that the beginning and substitute players' contributions to the team and their GI differed. The authors of [12] claimed that players displayed variations in their physical and technical-tactical characteristics based on the game situation. These specifications had to do with what every position in the game did.

Even though the previously discussed deep learning-based algorithms can identify basketball position, they frequently exhibit weak points when faced with complex contextual factors as shifting illumination, crowded

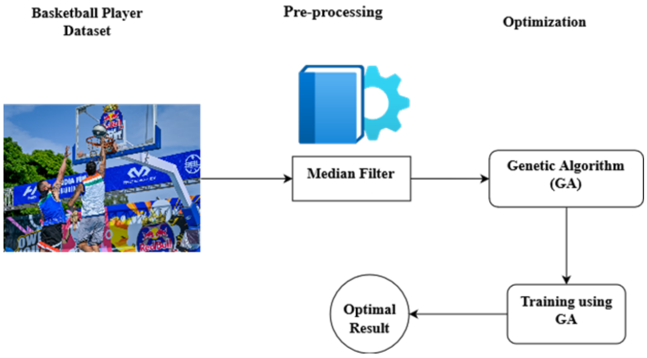

Fig. 3.1: Architecture of Proposed Method

backgrounds, and perspective alterations [19]. Furthermore, the basic design of the conventional C3D system makes it challenging to accurately detect basketball stance. Its effectiveness is therefore low, and the error rate is considerable. Furthermore, most of these methods require evaluating the entire movie or applying a classifier to each frame to assign just one action name to the entire video [3]. These methods are less effective than the human vision tactics, which can identify a scene from only one instance of visual input.

Considering these circumstances, this work investigates the use of cluster analysis and the association rule's method in the instruction of basketball in a mobile computing surroundings [16]. It does so in a way that will effectively encourage the use of these techniques in college physical education and serve as a guide for the improvement of physical learning in China. Because of the database's current security measures, users' interactions with the database are typical in real-world application settings. The standard access records for each user role are those kept in the database log. Various user jobs have quite diverse access behaviors [17].

3. Proposed Methodology. The proposed method for optimizing the plan and game strategy of basketball players using Genetic Algorithms (GA). Initially, the basketball players images or video is collected and then the data is pre-processed by using Median Filter. Next the GA method is used for optimizing the variables. Finally, the optimized variables are trained and predicted. In figure 1 shows the architecture of proposed method.

Predictive models are then trained using the variables that the GA has optimized. These models are made to predict the results of various training approaches, giving coaches and trainers the ability to evaluate possible effects prior to implementing training methods in full. Lastly, the training process incorporates the improved variables, allowing for the monitoring of their efficacy and the validation of predictions against real performance results. This cyclical cycle makes it possible to continuously improve tactics in light of actual performance, enabling a dynamic, data-driven, and adaptive approach to sports training.

3.1. Basketball Data Collection and Analysis. Basketball action identification is significant as it can assess player efficiency and give coaches and players feedback on areas that require development. It can also be utilized to help officials make better calls throughout games by examining the actions of players on the court to recognize fouls or other infractions that might have gone unnoticed. The extreme diversity in player motions and actions presents one of the biggest obstacles to action recognition in the game of basketball. Basketball matches feature numerous players running all over the court at once, which makes it challenging to follow each player precisely and identify their movements. Furthermore, a lot of basketball moves could appear similar yet, depending on the situation, have distinct meanings.

3.2. Pre-processing. Aside from the preprocessing procedure, the proposed model consists of two primary sections. During the data preparation process, basketball photos may have a significant amount of noise.

In this research, a median filter is applied as a stage of preprocessing to address this problem and reduce interference when identifying basketball activity from video pictures.

3.3. Optimization and Training using Genetic Algorithms. 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 Basketball Player analysis is to identify and select the best teaching techniques and achievements.

Encoding. Every person would be encoded as a chromosome, which is commonly shown as an array of numbers or a binary string. Every gene on a chromosome would stand for a choice variable, like whether a player gets chosen.

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

3.2.2 Initialization

Create a starting population (individuals) of possible solutions. This population may be created at random, using heuristics or previous knowledge as a basis.

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

Fitness Function. Create a fitness function that measures each player's (combination of players') performance according to the specified parameters. This function could consider several variables in the context of basketball player forecasting, including player roles, team science, opponent strengths, and player statistics (points scored, rebounds, contributions, etc.).

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

Selection. To produce the future generation, choose certain people from the existing population. People are usually chosen through a fitness-based procedure in which those who perform better are more likely to be chosen. Rank-based, tournament, and roulette wheel selection are examples of popular selection techniques.

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

Crossover. Select individuals should undergo crossover (recombination) to produce offspring for the following generation. To generate novel solutions, this entails the exchange of genetic material, or genes, between pairs of humans. The problem and the solution representation determine the crossover technique that is employed.

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

Mutation. To preserve diversity and investigate new areas of the search space, introduce random modifications, or mutations, to some members of the population. The algorithm is kept from becoming trapped in local optima by mutation. Mutations can occur when bits in binary strings are switched around or when chromosomal gene values are slightly altered.

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

Replacement. For several generations or until a termination condition (such as a maximum number of generations or convergence requirements) is satisfied, repeat the selection, crossover, and mutation processes.

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

The phases 3 through 7 of the GA process must be repeated iteratively to develop the solutions and get the highest fitness score.

This research makes it possible to create highly individualized training plans that are suited to the unique strengths and limitations of both the team and individual players by using GAs. Improved player development and more successful training results may result from this individualized strategy.

GAs offer a framework for continuously updating and improving strategies in response to performance data. This process is known as dynamic strategy adaptation. This flexibility keeps the squad competitive by guaranteeing that workout routines and game strategies work against diverse opponents and in variable settings.

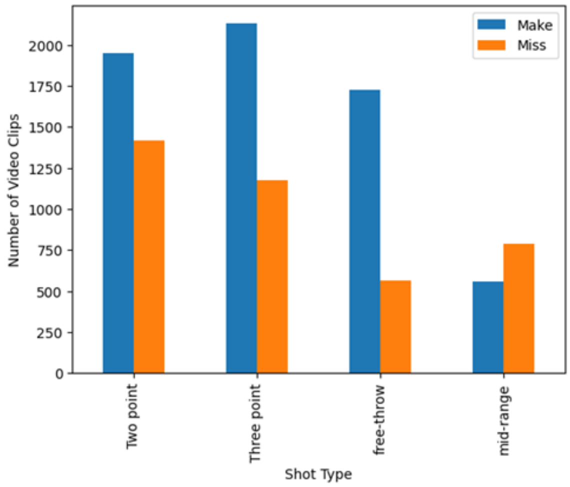

Fig. 4.1: Samples in each class on the Basketball-51 dataset

4. Result Analysis. The implementation of the suggested approach was carried out using two distinct datasets, Basketball-51 and SpaceJam, to verify its effectiveness. Two components comprise the basketball player activities found in the SpaceJam dataset. The joint locations of the single-player posture are shown in samples in the first part, which is referred to as the joint dataset. Every frame in RGB colours for every action is contained in the second portion, which is referred to as the clip database. Actions like walk, not doing anything, run, protection, dribbling, ball in hand, pass, block and select, and shoot are all included in this dataset. The completed datasets with annotations contain roughly 32,560 samples, which can be used as the basis for the training and testing stages.

The first dataset, referred to as the "clip Dataset," consists of 16 RGB frames that highlight a single participant in each case. The joint coordinates (x,y) of the participant on the picture plane are contained in the second dataset, referred to as the "joint Dataset," on the opposite side. Although the file extensions of the two datasets are different—joints are saved as numpy vector files (name file.npy), and clips are stored in compressed mp4 files (name file.mp4)—they share the same identifier for related examples.

The 10,311 video snippets from 51 NBA basketball matches make up the Basketball-51 collection. Third-party recording devices, commonly employed in sports broadcasting, recorded all the videos. The video footage was initially divided into eight class designations: mid-range shot miss, mid-range shot makes, free throw fail, free throws make, two-point miss, and three-point miss. Figure 2 shows the arrangement of data in the dataset according to several labels. the quantity of video clips, divided into categories based on the many basketballs shot kinds, including mid-range, free throw, three-point, and two-point. There are two bars for each type of shot, one for each shot that was made and one for missed. Shots that were made ("Make") are represented by blue bars, and shots that were missed ("Miss") are represented by orange bars. The number of successful (made) versus unsuccessful (missed) attempts for each type of shot can be compared. Although the actual numbers are not displayed in this description, such a chart usually enables readers to quickly compare these values.

When an algorithm for deep learning is being trained, the epochs stand for iterations across a dataset. We have epochs numbered 0 to just over 50 on the x-axis. Accuracy is represented by the y-axis, which runs from 0 to 1 (or 0% to 100%). Both lines begin with accuracy near zero, and both models get more accurate as the number of epochs rises. This is typical of machine learning models, which improve their accuracy in classifications or predictions as they 'learn' from more data across more epochs. Early in training, the "proposed model" line surpasses the YOLOv4 line and continues to perform better for the remaining epochs. It appears that both models' accuracy peaks around the 50th epoch, suggesting that further training after this may not yield appreciable gains in accuracy. In figure 3 shows the evaluation of training accuracy.

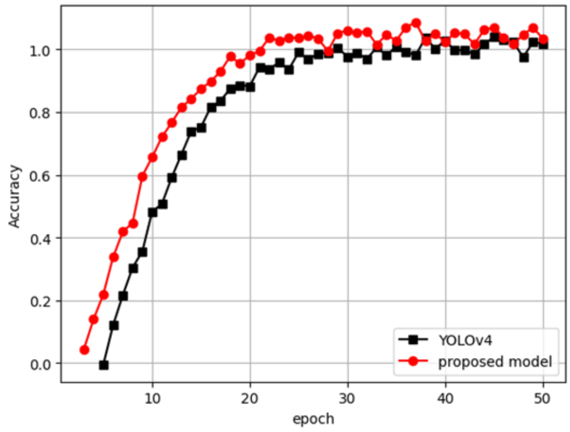

Fig. 4.2: Evaluation of Training Accuracy

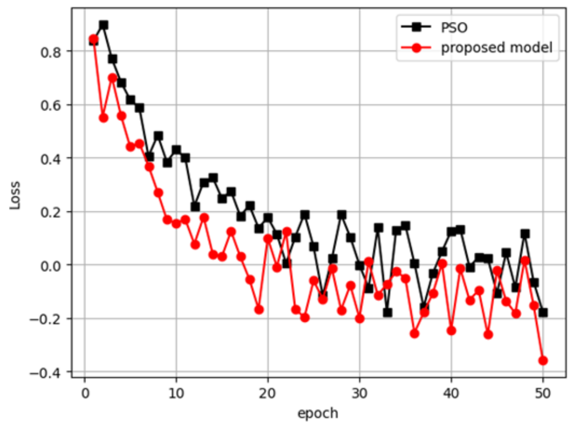

Fig. 4.3: Evaluation of Training Loss

The epoch number, which ranges from 0 to little over 50, is indicated on the x-axis. The error between the values that the model predicts and the actual values from the training data is typically shown by the y-axis, which measures loss. During machine learning training, minimizing this loss is usually the aim. Both models have an initial larger loss (about 0.6 for the proposed model and closer to 0.8 for PSO), which generally decreases as the number of epochs rises. This suggests that the models are learning and developing.

The suggested model, whose loss curve displays more notable ups and downs, is the only one on the graph that displays significant changes in the loss. This can point to fluctuations in the training procedure or noise in the training set. Eventually, the loss values of both models approach or fall below zero, with the suggested model sporadically falling below zero. This could indicate overfitting or a mistake in the loss computation. In figure 4 shows the evaluation of Training Loss.

In Figure 5,6 shows the confusion matrices of the suggested model for subject-dependent and independent classification techniques based on recollection and classification reports. Most misclassifications are found to occur in the mid-range area, where shots are typically labeled as two- or three-point attempts. This might be explained by the imbalance in the dataset, which has more 2- and 3-point data clips than mid-range ones. Lower performance may also be caused by the same similarity of interclass activities and the absence of a clear range differentiation between various ranges. The suggested approach much outperforms previous groups in

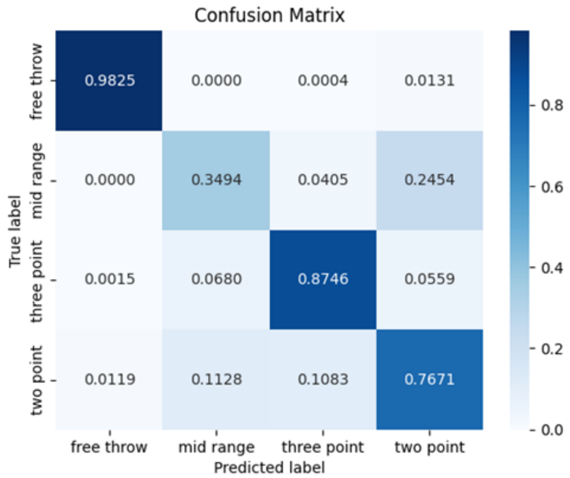

Fig. 4.4: Confusion Matrix for Subject Dependent Basketball-51 dataset

identifying free throw characteristics with high accuracy.

The Predicted Labels are represented by the x-axis, and the True Labels are represented by the y-axis. These labels match the categories that the model is predicting, which in this example are the many kinds of basketball shots that can be made free throw, mid-range, three-point, and two-point. The heatmap's right side features a color scale that shows the range of values inside the matrix: 1.0 (red) denotes a higher frequency of predictions, while 0.0 (blue) denotes a lower frequency. Every cell in the heatmap represents the likelihood (or frequency) of the model's predictions.

At the intersection of the 'free throw' (genuine Label) and 'free throw' (Predicted Label), there is a dark red cell with a 0.9549 value, suggesting a high frequency of accurate predictions in cases when the genuine shot turned out to be a free throw. On the other hand, a low-value cell is coloured blue, suggesting that the model seldom misclassifies a two-point shot as a free throw. An example of this would be the cell at the intersection of "two point" (True Label) and "free throw" (Predicted Label). The diagonal cells of a perfect confusion matrix, which run from top left to bottom right, should have the greatest values (darker red), signifying that the model correctly predicts the actual class labels. Misclassifications are shown by off-diagonal cells with greater values. In figure 6 shows the confusion matrix for Subject Independent Basketball-51 dataset.

5. Conclusion. The success of basketball teams is largely dependent on how well their practice routines and game strategies work. It is quite challenging to create efficient training regimens and tactical strategies due to the complexity of the game and the variety of talents players need to possess. This paper investigates how basketball players might improve their practice routines and game strategy by using genetic algorithms (GAs), a cutting-edge technique. Genetic algorithms are powerful optimization techniques that, via the iterative processes of evolution, can find almost perfect solutions to difficult problems. These algorithms draw inspiration from biology and natural selection. Prospective training strategies and game tactics are represented by GAs, which are chromosomes composed of genes pertaining to various parameters and tactics. This allows GAs to search the vast solution space effectively and identify combinations that maximize desired outcomes. The objectives of the optimization problem and its constraints are specified as part of the research methodology. Fitness functions are designed to evaluate the effectiveness of each possible solution, guiding development toward more effective solutions through a series of iterations. Using simulators and actual testing, this study demonstrates the efficacy of genetic algorithms in optimizing basketball players' training plans and game strategies. Coaches can use GAs to iteratively adapt and adjust tactics based on feedback and performance data, ultimately enhancing player growth and team competitiveness. The study's findings are relevant to team sports other than basketball, where players' individual skills, teamwork, and strategic decisions all interact to greatly impact

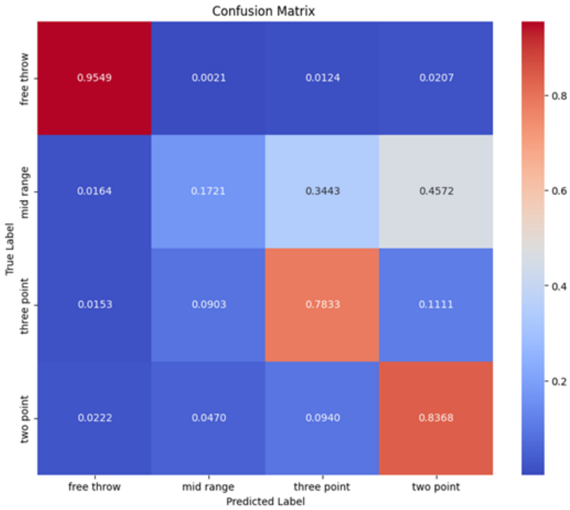

Fig. 4.5: Confusion Matrix for Subject Independent Basketball-51 dataset

outcomes. Ultimately, applying genetically based algorithms to sports analytics offers a practical means of refining coaching methods and achieving optimal performance in athletic environments.

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