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The Application of Artificial Intelligence and Big Data Technology in Basketball Sports Training

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Abstract

INTRODUCTION: Basketball involves a wide variety of complex human motions. Thus, recognizing them with Precision is essential for both training and competition. The subjective perceptions and experiences of the trainers are heavily relied upon while training players. Big data and Artificial Intelligence (AI) technology may be utilized to track athlete training. Sensing their motions may also help instructors make choices that dramatically improve athletic ability.
OBJECTIVES: This research paper developed an Action Recognition technique for teaching basketball players using Big Data, and CapsNet called ARBIGNet
METHODS: The technique uses a network that is trained using large amounts of data from basketball games called a Whale Optimized Artificial Neural Network (WO-ANN) which is collected using capsules. In order to determine the spatiotemporal information aspects of basketball sports training from videos, this study first employs the Convolution Random Forest (ConvRF) unit. The second accomplishment of this study is creating the Attention Random Forest (AttRF) unit, which combines the RF with the attention mechanism. The study used big data analytics for fast data transmissions. The unit scans each site randomly, focusing more on the region where the activity occurs. The network architecture is then created by enhancing the standard encoder-decoder paradigm. Then, using the Enhanced Darknet network model, the spatiotemporal data in the video is encoded. The AttRF structure is replaced by the standard RF at the decoding step. The ARBIGNet architecture is created by combining these components.
RESULTS: The efficiency of the suggested strategy implemented on action recognition in basketball sports training has been tested via experiments, which have yielded 95.5% mAP and 98.8% accuracy.

Keywords: Big Data, Artificial Intelligence (AI), Whale Optimized Artificial Neural Network (WO-ANN), Action Recognition with Big Data and CapsNet (ARBIGNet)

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1. Introduction

In today's world, when people have more time and money to devote to leisure activities, sports are becoming more popular. Athletes are more likely to stay healthy and prevent injury when they exercise often, and this makes sense, given the research showing that exercise improves an athlete's mood and feeling of well-being while also bolstering the immune system [1]. Those who put in the time and effort to become better athletes almost always succeed. Adolescents may benefit significantly from participating in team sports since they foster the growth of healthy social connections, aid in the development of communication and coordination skills, and teach the importance of working together to accomplish a shared objective [2]. Sport has tremendous aesthetic value and the ability to improve people's lives. People like gathering in front of the TV to watch their favorite sports teams compete. Sports events, notably basketball games, have recently increased in popularity. Because athletes come in various shapes, sizes, and skill sets, training methods must be individualized [3]. There is a growing need for qualified coaches and training methods supported by sound scientific research as more and more individuals take up sports as a recreational activity. It is widely accepted that coaches must see their athletes perform in their natural environment before formulating an effective training plan. Some of the significant issues with this approach are listed below. Most importantly, it makes it harder for coaches to learn new techniques and strategies in their sports and to come up with fresh ideas for forthcoming practices [4]. As a consequence, there is now a critical shortage of trained teachers. Another is that managers who look simply at the numbers need to learn more about their players. Speed, acceleration, and angular velocity are the quantifiable variables represented in the data. In basketball, a team may get a point by making a shot or preventing the other team from doing so. Compared to ball sports like soccer and volleyball, which emphasize skill and method, basketball features more intra-team conflict and coordination [5]. A basketball team's success or failure depends heavily on its members' skills. When crucial members of a team lack essential talents, the defense and offense suffer. This highlights the need to provide players with data-driven, in-depth basketball coaching. Training plans are often influenced by coaches' notes from games and practices. Since the technique is grounded in the coaches' perspectives and anecdotes, it is inherently subjective [6]. In order to evaluate the success of their training, coaches must manually compare athlete performance to various metrics. However, keep in mind that there are limitations to this approach. So, collecting sports data and player movements in real-time is essential for improving players' ability to compete and coaches' ability to judge [7].

With the advent of Artificial Intelligence (AI) , a new era of discovery has started (AI). Massive datasets are essential to the development of artificial intelligence. Artificial intelligence (AI) is a crucial resource for giving direction and amassing rules when it comes to big data. AI is far more efficient than humans in processing large datasets. As robots can outthink humans logically, they may use deep iterative learning to make predictions and judgments. Some scientists in the field of sports have already begun using artificial intelligence (AI) technologies for motion recognition [8]. The results of this research will likely be used by coaches who are not present at the competition to get insight into the performances of several competitors quickly. As a result of this simplification, more athletes will benefit from coaches' knowledge and guidance throughout their training. As part of this research, we developed a network to identify basketball-related activities. The technique uses an artificially trained neural network with information on basketball [9]. The proposed method uses basketball training videos to extract spatiotemporal information. We employ the ConvLSTM architecture to decode movies using the Darknet network model and extract valuable spatiotemporal data. Decoding is performed using an AttLSTM structure rather than a standard Long Short-Term Memory Networks (LSTM). These parts are put together in the BSTARNet architecture to make a system reliably detect action during basketball practices [10].

Using deterministic finite automata, we offer a system for recognizing the behaviors of sports participants and authorities in video clips. Researchers were able to correctly recognize events in football game recordings using a 2D and 3D convolution neural network (CNN). Experiments have revealed that three-dimensional convolutional neural networks (CNNs) are superior to two-dimensional CNNs in terms of recognition accuracy [11]. Findings from this study show that 3D CNN is superior to 2D CNN in extracting important features from data. Scientists keep an eye on everything using a plethora of cameras. It is more difficult to determine who performs when they are just partly visible [12]. This approach may help fix the problem. Particles in the model field may capture target dependencies in a state-space model by integrating appearance and motion models. This method is also helpful for multi-target monitoring, which is utilized in football and other team sports with similar physical qualities and unexpected moves to keep track of many moving objects at once [13]. Extreme classifiers trained on massive datasets could assist sports fans in organizing videos, emphasizing key moments, and quickly locating clips they want to watch again. Consumers need tools that can highlight and summarize the most crucial aspects of sports videos. The author claims that he analyses both teams' link and ball possession data on a deep extreme learning machine and then adapts the strategy appropriately [14]. Adding spatial information to the time series data helped the algorithm figure out where players were and what they were doing. The projective transformation was used to get the coordinates of the pictures.

Predictions for each part are combined to form a complete video forecast. The study's authors believe that C3D is a practical feature extractor because it effectively adapts 2D convolution and pooling to the topology of a 3D network [15]. Taking the 2D convolutional neural network model into the 3D realm, the authors propose I3D, which incorporates a time dimension into all convolution kernels and pooling layers. The author recommends utilizing a Posture Normalized CNN technique to complete posture alignment operations based on images [16]. To improve recognition performance, it is suggested that the classification network and the APN network be integrated, as shown by the outcomes of the RA-CNN study. An accelerometer and gyroscope were attached to it in order to monitor the basketball player's hand motions during a jump shot. When performing the four steps of a jump shot, athletes rely on an audible signal to help them maintain the correct shooting stance. Exemplification of the Jump Shot Form He moves his arms and legs in unison with the rest of his body [17]. The only thing that counts for a successful shot is where the shooter's hand is. We assessed the physiological features of basketball players by monitoring and comparing various variables, including heart rates, oxygen consumption rates, and acceleration rates. Although there has been a need for more research in basketball measuring, this discovery implies that wearable sensors may be a beneficial tool. Researchers used acceleration sensors to develop a posture detection system for basketball, classifying players' leg movements into eight categories [18]. Coaches need results from various tests to gauge their athletes' development. Keeping track of game results and other metrics in real-time is a challenge for coaches in any sport. The proposed method uses basketball training videos to extract spatiotemporal information [19]. We employ the ConvLSTM architecture to decode movies using the Darknet network model and extract valuable spatiotemporal data. Decoding is performed using an AttLSTM structure rather than a standard LSTM. The BSTARNet architecture incorporates these elements into a cohesive system for dependable action detection in basketball practices. A convolution neural network (CNN) may replicate the hierarchical data processing in the visual cortex by using pooling layers, convolutional layers, and classifiers [20]. When CNN is given an image or video as input, the higher-level convolutional layer is responsible for identifying and extracting abstract fusions of various underlying properties. In contrast, the lower-level convolutional layer detects and extracts the most basic graphical elements. It would only operate as intended if the network had a convolutional layer. Effective convolution kernels only interact with neighboring picture components [21]. The purpose of the pooling layer, which comes after the convolution layer, is to lower the feature map's resolution without reducing its depth. Maximum pooling and mean pooling are two common approaches used to speed up learning and reduce the number of parameters in training [22]. We may do classification and recognition using the fully connected layer by adapting the feature map to the classifier's preferred input format. The LSTM neural network was created to fix problems with conventional recurrent neural networks [23]. Three gates—an input gate, a forget gate, and an output gate—control the operations of this sophisticated RNN. Information that has to be forgotten or deleted is done by the forget gates, while the input gates decide how much data is transmitted to the next hidden state. In the current LSTM, there are three "switches" that may be toggled depending on the situation: one for saving information for later use, one for entering the current state instantly, and one for choosing whether or not to use the previously stored information for the output [24]. This study evaluates the application of artificial intelligence and big data technology in basketball sports training.

Basketball includes a wide range of intricate human actions, thus being able to accurately identify them is crucial for both practice and competition. While teaching athletes, coaches often rely on their own impressions and experiences. Big data and Artificial Intelligence (AI)-based technology may be used to monitor an athlete's training. It may also assist teachers in making decisions that significantly enhance students' athletic prowess by detecting their movements.

Contribution of the work

- ARBIGNet, a method for training basketball players Action Recognition, was created in this research study utilising Big Data and CapsNet. The method employs a network called a Whale Optimized Artificial Neural Network (WO-ANN), which is trained using a lot of data from basketball games and is gathered utilising capsules.
- This work uses the Convolution Random Forest (ConvRF) unit to first identify the spatiotemporal information components of basketball sports training from films. The development of the Attention Random Forest (AttRF) unit, which integrates the RF with the attention mechanism, is the second achievement of this research.
- Big data analytics were employed in the research to transmit data quickly. The device randomly scans each location, concentrating more on the area where the activity is occurring.
- The network design is refined by improving upon the traditional encoder-decoder paradigm. Finally, the geographical and temporal data in the movie are encoded using the Enhanced Darknet network model. AttRF structure is employed instead of the regular RF throughout the decoding process. The ARBIGNet architecture is the sum of these pieces.

2. Related Work

The capacity to effectively identify a wide variety of complex human movements is crucial in competition and training for the sport of basketball. A coach's observations and experiences are highly influential while training athletes. Technologies like artificial intelligence and large data sets can be used to track how hard athletes are working. In addition, it can help coaches make judgments that will considerably improve their athletes' abilities by monitoring how they move. As part of his dissertation, Si Zhong (2022) created a system called BSTARNet, an action recognition approach to basketball sports instruction. Artificial neural networks (ANN) form the basis of the process, with the network being trained using data from the world of professional basketball [25]. The Convolution Long Short-Term Memory (ConvLSTM) unit extracts spatiotemporal information aspects of basketball sports training from videos. Second, the Attention Long Short-Term Memory (AttLSTM) unit, which integrates the attention mechanism with the LSTM, is established in this work. The system can choose which areas to scan, mainly focusing on where the action is taking place.

At last, the network architecture is constructed by enhancing the standard encoder-decoder paradigm. The video's spatial and temporal data are then encoded using the Darknet network model. The AttLSTM architecture is used to substitute for the regular LSTM during decoding. The BSTARNet framework is composed of these individual components. We undertake experiments to validate the efficacy of the suggested method applied to action recognition in basketball sports training and find that we can reach 95.4% accuracy and 89.5% mAP.

Studying how artificial intelligence (AI) can be used to detect motions during basketball practice is the primary goal of the research conducted by Yao Cheng et al. (2022). The theory of somatosensory gesture recognition is primarily examined, providing a theoretical basis for further study. To guarantee that the obtained signal data is not distorted, the collected signal is denoised and normalized. Finally, the data of athletes' various limb movements and recollections are detected using the four algorithms Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), And Artificial Neural Network (ANN). Data precision is evaluated via comparison and analysis. Our experimental results conclude that back propagation (BP) is the most effective of the four ANN algorithms regarding action recognition. The average accuracy rate for detecting upper limb movements among basketball players in training is nearly 93.3%, with an immediate recall average of close to 93.3% [26]. The average accuracy rate for detecting lower limb movements among basketball players in training is close to 99.4%, with an immediate recall average of 99.4%. The recognition method has a recognition rate of over 95%, and the average accuracy of the four training actions of catching, passing, dribbling, and shooting is close to 98.95%, demonstrating its efficacy in detecting the movements of the upper and lower limbs necessary for playing basketball. The research on an intelligent basketball training system will assist coaches in better understanding their players' skilled movements, leading to more effective training programs and, ultimately, better players.

Outsourced data storage must meet two crucial requirements: data privacy and data usefulness. Data encryption and other traditional methods of safeguarding private information reduce the speed with which data may be queried and analyzed. Database fragmentation strategies may safeguard personal information and boost data value by severing sensitive relationship features. In order to improve the security and usability of databases, a DMA is recommended in this article [27]. To maximize optimization effectiveness, we develop a framework based on a balanced best random distribution. In order to improve global search, we propose a dynamic grouping recombination operator that can collect and use evolutionary elements; we design two mutation operators, merge and split, to aid in the arrangement and creation of evolutionary elements; and we develop a two-dimensional selection approach that prioritizes privacy and utility. A splicing-driven local search technique is also used to sneak in uncommonly-used components without breaking any rules. For the purpose of ensuring the efficacy of the planned DMA, extensive trials are conducted.

By separating sensitive association characteristics into chunks, database fragmentation protects distributed database privacy [28].The distributed database's initial fragmentation cannot last forever. This work describes a dynamic database fragmentation issue with privacy preservation criteria, optimizing for privacy preservation degree and communication cost. To minimize communication cost and preserve privacy, KT-DDE is suggested for this situation. KT-DDE uses a distributed architecture and differential evolution-based optimizer. The distributed system transfers fragmentation knowledge amongst database fragmentation subproblems. The optimizer generates trial people using fragmentation data from several individuals. Competitive trial participants remain after selection. Experimental findings reveal that the proposed approach outperforms rivals in solution correctness, convergence speed, and compute economy. The components' efficacy is also confirmed.

Database fragmentation protects privacy by separating properties with sensitive relationships. Multi-relational databases are common. Each relation is fragmented sequentially. Hence, database fragmentation methods treat each relation fragmentation issue separately. While tackling multiple fragmentation issues, duplicate computing resources are used to extract fragmentation information, limiting algorithm performance. This study formalizes a privacy-preserving multitasking database fragmentation issue. A multitasking distributed differential evolution method with two new operators is presented. The system exchanges general and effective allocation information amongst database fragmentation concerns. Several database fragmentation solutions may alter fragment ordering using a similarity-based alignment operator[29]. A perturbation-based mutation operator with adaptive mutation strategy selection is developed to adequately share evolutionary information in solutions. The suggested approach outperforms rivals in solution accuracy, convergence speed, and scalability, according to experiments.

The purpose of this research was to demonstrate the utility of AI methods in sports using weightlifting as an illustration. Particular attention was paid to the use of pattern recognition techniques for measuring the effectiveness of workouts on fitness equipment. Data was collected by attaching way and cable force sensors to a variety of weight equipment in order to monitor critical displacement and force variables during workouts. Other important properties, such as time periods or movement velocities, could be inferred from the collected data. Incorporating these factors into the design of intelligent methods modified from traditional machine learning ideas enabled autonomous assessment of exercise technique and feedback to be given to individuals in real time. The application of such methods may be indispensable in the future for studying performance, helping not only athletes but also coaches, optimizing training, and preventing injuries. Measurements for the current study were taken from 15 very novice volunteers who completed three to five sets of ten to twelve repetitions on a leg press machine [30]. Important features were extracted from the initially preprocessed data using supervised modeling techniques. Expert trainers participated in the grading and categorizing processes by watching the recorded performances. Modeling findings produced to date have shown promising performance and prediction outcomes, suggesting the viability and efficacy of using AI approaches to automatically assess performances on weight training equipment and provide sportsmen with timely advice.

In the areas of categorization and prediction, machine learning (ML) is one of the intelligence approaches that has demonstrated promising outcomes. Sports betting, being a growing industry, places a premium on reliable predictions because of the high stakes involved. Furthermore, club managers and owners are seeking classification models in order to comprehend the nuances of the game and devise winning plans. These models take into account a wide variety of variables, including past game outcomes, individual player statistics, and opponent data. R.P. Bunker et al. (2019) give a review of the research on Machine Learning (ML), zeroing on on the use of ANNs to forecast sporting outcomes. By doing this, we are able to pinpoint the learning approaches taken, the data used, the best ways to evaluate the models, and the unique difficulties involved in making accurate predictions for sporting events. Because of this, we present a new framework for making predictions in the world of sports using machine learning [31]. The Authors believe that researchers who delve into this field in the future will find our work both enlightening and useful.

Computer information technology has spread throughout many sectors of American society as a result of the rapid development of science and technology over the past few decades. The use of AI in the form of computer-assisted teaching has the potential to significantly improve the structure and methodology of basketball training. In this study, authors Y Zhao and J Xie describe the ideas behind AI-based computer-assisted teaching technology and discuss its primary role in the context of practical basketball training and instruction (2017). Meanwhile, the specifics of basketball training, including the use of AI, were spelled out in greater detail. Last but not least, a questionnaire survey was used to examine the findings of the investigation into the use of AI computers for assisting with basketball training. In order to achieve the desired result, two things must occur [32]. One must have a fundamental familiarity with the state-of-the-art implementation of AI-based, computer-assisted teaching technology in China's basketball instruction. One more is to identify technological issues related to basketball practice. By doing so, we hope to increase students' interest in the sport of basketball and point the way for future advancements in the use of AI in computer-assisted instruction.

3.Proposed methodology

This study introduced a new action recognition method, termed ARBIGNet thatcan be used to better instruct basketball players by collecting the player’s movement with the support of capsules of CapsNet. The method employs a Whale Optimized Artificial Neural Network, a network trained with extensive data from basketball games (WO-ANN). This study creates the ARBIGNet, an action recognition system for basketball instruction using CapsNet. This process is built on an artificial neural network, and massive data from basketball-related events is used to train the network. In this study, the Convolution Random Forest (ConvRF) unit is initially used for the purpose of identifying key time and space characteristics of basketball practice sessions via video analysis. The second result of this research is the Attention Random Forest (AttRF) unit, which integrates the RF with the attention mechanism.

3.1Convolution Random Forest (ConvRF) unit

The advantages of both CNN and RF are taken into account in the hybrid CNN-RF model, which employs RF to classify the high-level characteristics collected by the CNN. CNN-classification RF's input is based on spatial information retrieved from the best CNN structure and parameters. This means that there is no need for a feature extraction or selection phase before the RF-based categorization. RF employs more complex classification algorithms, such as packing, than CNN's fully connected layer as a classifier. Further, when accurate or relevant spatial features cannot be retrieved from CNN due to insufficient training data and input images, the classification performance can be improved by utilizing RF's benefits, such as its resistance to outliers as well as its ability to reduce overfitting (Figure 1).

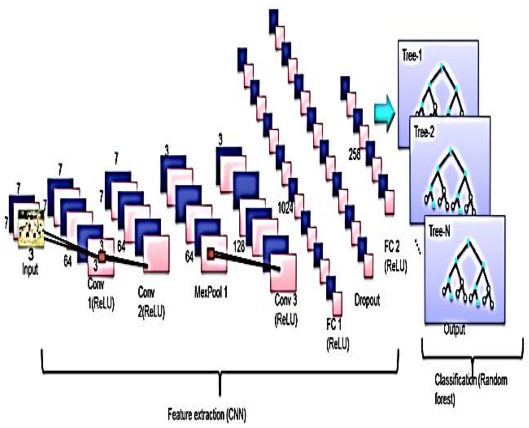

Figure 1. Architecture of the proposed CNN-RF with CapsNet

3.2 Attention-based Random Forest (AttRF) unit

First, we will officially state the common regression issue. In machine learning, the goal is to build a regression model f(x) that minimises some thr eshold for error, such as the least - square error. By using big data, the errors can be minimized with the utilization of CapsNet is depicted in Equation (1).

$$\frac{1}{n}\sum_{i=1}^{n}(y_i - f(x_i))^2 \qquad (1)$$

To solve both classification and regression problems, RFs can be seen as a potent nonparametric statistical tool.

Let's pretend that T decision trees make up an RF. The significance of the last requirement lies in the fact that it precludes a single instance from fitting into multiple branches of the same tree. To further clarify, let's define the mean target value Bk as the average of training instance vectors that reside on the i^{th} leaf of the k^{th} tree, and then introduce the mean vector Ak(x) as the average of the corresponding observed outputs is presented in Equation (2).

$$A_k(x) = \frac{1}{\#J_i^{(k)}} \sum_{j \in J_i^{(k)}} x_j, \tag{2}$$

$$B_k(x) = \frac{1}{\#J_i^{(k)}} \sum_{i \in J_i^{(k)}} y_j, \tag{3}$$

Since there is exactly one leaf that can contain the instance x, the index I of the leaf is not used in the notation of $A_k(x)$ and $B_k(x)$.The definition of these parameters are presented in the Equation (2) and Equation (3). Let's pretend that T trees have been planted in the RF. Keep in mind that there is only one leaf in each tree that the instances can fit into.For a given testing instance x, the final RF prediction y is defined as in the basic regression RF as in Equation (4).

$$\hat{y} = \frac{1}{T}\sum_{k=1}^{T} \hat{y}_k = \frac{1}{T}\sum_{k=1}^{T} B_k(x) \tag{4}$$

The above forecast presumes that all trees contribute equally to the final forecast, that their weights are equal, and that$1/T$. However, it is clear that the distance between x and $A_k(x)$ varies, which may have an effect on y in unexpected ways. Thus, we can implement tree weights, giving more importance to trees that have a smaller distance since they improve accuracy, and vice versa. This leads us to the following issue, which is how to properly specify tree hefts.

Rephrasing the original formulation of the Nadaraya-Watson regression method in terms of the RF yields the Equation (5).

$$\hat{y} = \sum_{k=1}^{T} \propto (x, A_k(x), w). \hat{y}k = \sum_{k=1}^{T} \propto (x, A_k(x), w). B_K(x). \tag{5}$$

Here, $(x, A_k(x), w)$ is the focus weight that agrees with the "mean instance" $A_k(x)$ to vector x and fulfils the condition using CapsNet as in Equation (6).

$$\sum_{k=1}^{T} \propto (x, A_k(x), w) = 1 \tag{6}$$

Below, we shall define w, a vector of trained concentration parameters, in light of the new model. Finally, the trainable attention-based RF with parameters w is obtained by minimizing the predicted loss function across a range of W parameters using CapsNet as shown in Equation (7).

$$W_{opt} = arg\ min_{w\epsilon W} \sum_{s=1}^{n} L(\hat{y}_s, y_s, w) \tag{7}$$

To reformat the loss function using CapsNet, one can use the following in Equation (8).

$$\sum_{s=1}^{n} L\,(\hat{y}_s, y_s, w) = \sum_{s=1}^{n} y_s - (\sum_{k=1}^{T} \propto (x, A_k(x_s), w).)^2$$
$$= \sum_{s=1}^{n} \quad \left(y_s - \sum_{k=1}^{T} \propto (||x, A_k(x_s)||^2, w) B_k(x_s)\right)^2$$
(8)

Using the feature weights has the potential to vastly improve the performance of the model using CapsNet, as demonstrated by our preliminary numerical testing.So, we may reformulate Equation (8) as in Equation (9).

$$\sum_{s=1}^{n} L\,(\hat{y}_s, y_s, w, z) =$$
$$\sum_{s=1}^{n} \quad \left(y_s - \sum_{k=1}^{T} \propto \left(|\left|(x_s - A_k(x_s))0z\right||^2, w\right) B_k(x_s)\right)^2$$
(9)

Hadamard product of vectors is indicated here by the symbol "o". How to design the function and determine the observable parameters w and z that can be trained is the next challenge. There are three variations of ABRF, and each one is associated with a certain function.

3.3 Whale Optimized Artificial Neural Network (WO-ANN)

The action recognition technique for teaching basketball players is a double class classification problem. To that end, we're on the lookout for a way to cut down on them. As can be seen in figure 2, we use a hybrid approach consisting of a multi-layer ANN and a WO optimization technique, we suggest a hybrid approach to teaching basketball players. Since each record in the data contains 48 features, an artificial neural network (ANN) is constructed using 48 input neurons, a single output neuron to indicate the gender of an email's sender, and 2 hidden layers comprised of 20 and 11 neurons, accordingly, in the first and secondary layer, both with a Nonlinear activation. Unlike prior studies, which relied on statistical methods when choosing weights and biases for ANN, our suggested approach uses WOA to get optimal results.

Biases and weights were fine-tuned to perfection for each iteration of both the ANN-WOA algorithm, with the weights and biases being treated as members of the whale population. Next, ANN is trained again using the updated weights and biases. This is done over and over again until the desired Precision is reached. WOA analyses the current condition of the problem to determine its best course of action. This inquiry simultaneously searches both locally and globally across the problem space. With this feature, WOA has outperformed other evolutionary algorithms including the genetics algorithm, particle swarm optimization, and the bat algorithm when it comes to solving optimization problems. Figure 2 depicts how WOA evaluates new weights and biases at each iteration; the weights and biases that result in the lowest classification error are used to build the ANN. For this reason, WOA takes part in ANN's learning to increase its categorization precision. The data is classified using the aforementioned ANN-WOA hybrid approach.

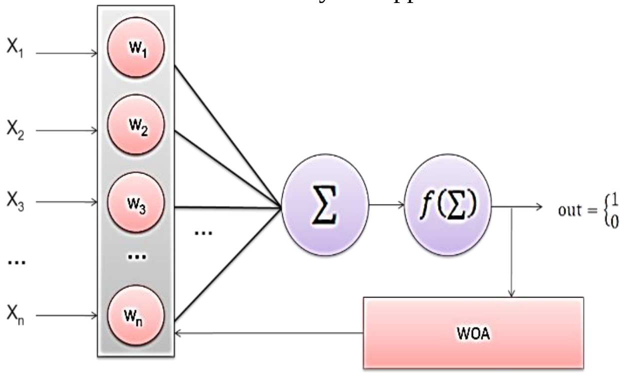

Figure 2. WOA to pick the right weights and biases for ANN

CapsNet structure is used for text classification in sports training. The data contains videos and images of sports training. The given text are convolutes to Equation (10).

$$teEXPf_1, teEXPf_2, \dots, teEXPf_k \quad (10)$$

be the output vectors coming from the capsules of the below layer. By using the neural network, the vectors $\mathrm{teEXPf}_1, \mathrm{teEXPf}_2, \dots, \mathrm{teEXPf}_k$ are sent to all possible parents. The vectors $\mathrm{teEXPf}_1, \mathrm{teEXPf}_2, \dots, \mathrm{teEXPf}_k$ are multiplied by corresponding matrix $\mathrm{wgU}_{ij}, \mathrm{i} = 1,2, \dots, \mathrm{k}$ that encodes important spatial and other relationships between the lower level capsules (letters, numbers) into the higher level capsules (text, numbers) of CapsNet. That is, in layer m the output vector teEXPf_i of the i^{th} lower capsule letters is fed into all capsules in the higher level capsule (text expression) $\mathrm{m}+1$ of CapsNet. The resulting vector $\widehat{\mathrm{EXPf}}_{j|i}$ is capsule i at level m's transformation of the entity represent by capsule j at $\mathrm{m}+1$ level of CapsNet. Then the predicted vector of the higher level as in Equation (11).

$$te\widehat{EXP}f_{j|i} = wgU_{ij} teEXPf_i \quad (11)$$

The above equation indicates the initial capsule i contributes to the capsule j in CapsNet. A weighted sum tet_j with weights wgv_{ij}, then the following Equation (12).

$$tet_j = \sum_{i=1}^{k} wgv_{ij} te\widehat{EXP}f_{j|i} \quad (12)$$

Where v_{ij} is the coupling coefficient that ensures the prediction of i to j in the layer level mto $\mathrm{m}+1$. Then calculate the candidates for the squashing function teu_j as in Equation (13) with CapsNet.

$$squash\ fn\ teu_j = \frac{\left\|tet_j\right\|^2 tet_j}{1 + \left\|tet_j\right\|^2 \left\|tet_j\right\|} \quad (13)$$

The above equation (13) is squashing function to the scalar vector between zero and unit length and also the vector direction is not change and tet_j is the input vector of the j^{th}capsule in CapsNet and the norm of the vector tet_j is the length of the module. Suppose tet_j is short. Then the following Equation (14) is obtained.

$$squash\ fn\ teu_j \approx \left\|tet_j\right\| tet_j \quad (14)$$

Suppose tet_j is long (that is, unit vectors). Then the following Equation (15)

$$squash\ fn\ teu_j \approx \frac{tet_j}{\left\|tet_j\right\|} \quad (15)$$

The coupling coefficient $\mathrm{wgv}_{ij}$is defined by as in Equation (16).

$$coup\ coe\ of\ wgv_{ij} = \frac{\exp\,(tew_{ij})}{\sum_k \exp\,(tew_{ik})} \quad (16)$$

The above equation determined by iterative dynamic routing process and w_{ij} calculating as in Equation (17).

$$tew_{ij} = tew_{ij} + te\widehat{EXP}f_{j|i}.(squash\ fn\ teu_j) \quad (17)$$

all capsule i in layer m and capsule j layer $(\mathrm{m}+1)$ level. The objective functions of the text and number classification of block chain of the optimized CapsNet as in Equation (18).

$$te\ L_M = teT_m max(0, mam^+ - \|tet_m\|)^2 + \mu\,(1 - teT_m) max(0, \|tet_m\| - mim^-)^2 \quad (18)$$

Where teT_m represents m th target label and $\|\mathrm{tet}_m\|$ is the length of m th digit capsule.
$\max^+$- maximum margin;mim^- - minimum margin; μ-weight factor; the total loss is denoted by teL_M and is equal to the sum of the losses of all digit capsules in CapsNet.

The data is split into a training set and an evaluation set at random. There is a 70% success rate in the training phase, and a 30% success rate in the testing phase. Multi-layer ANN is trained with training data and then tested on test data to see how well it performed. When training an

ANN, a WOA is used to reduce the output error as much as possible. In order to find the optimal weights and biases, ANN and whale are shown communicating with each other via an arrow. The WOA's mission is to aid the ANN in achieving accuracy in its gender detection.

4.Results and findings

In this study, big data technology is used to crawl basketball sports training videos from websites. There are a total of 1086 videos, 100 different basketball training staff performing each type of action in various scenarios. The remaining 409 videos are chosen as the test set, leaving 677 videos as the training set in this study. Accuracy and mean Average Precision (mAP) are the evaluation criteria.

A quantitative comparison is made between the suggested method and cutting-edge techniques to verify its validity. The experimental outcomes are depicted in figure 3; the contrasted approaches include LRCN [34], ALSTM [35], VideoLSTM [36], and CHAM [37]. When compared to previous approaches, the ARBIGNet suggested in this study can reach 90.5% mAP and 96.5% accuracy, which may be enhanced to varied degrees, demonstrating its superiority.

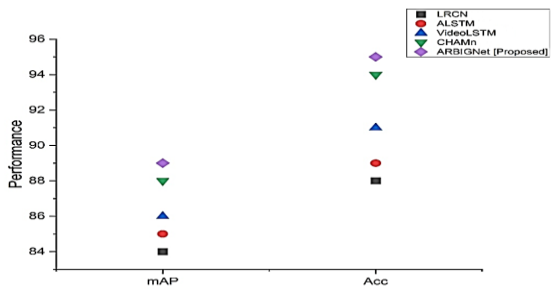

Figure 3. Comparison results of ARBIGNet with existing methods

Convolution and RF are combined in this study to create the ConvRF unit. Figure 4 shows the results of comparing the performances of this unit with and without ConvRF in order to confirm its efficacy. The two performance metrics may be enhanced by 1.3% and 1.1%, respectively, after employing the ConvRF unit, demonstrating its viability.

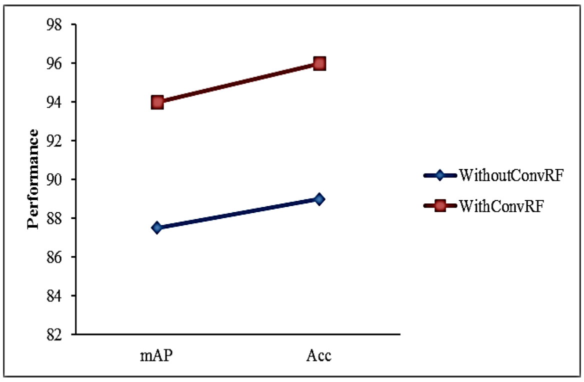

Figure 4. Comparison results of ConvRF

In order to create the AttRF unit, this work embeds the attention mechanism inside the RF. Performances with and without the AttRF unit is compared, and the experimental findings are shown in figure 5, to confirm the usefulness of this unit. The two performance metrics may be improved by 1.7% and 1.5%, respectively, after employing the AttRF unit, demonstrating its viability.

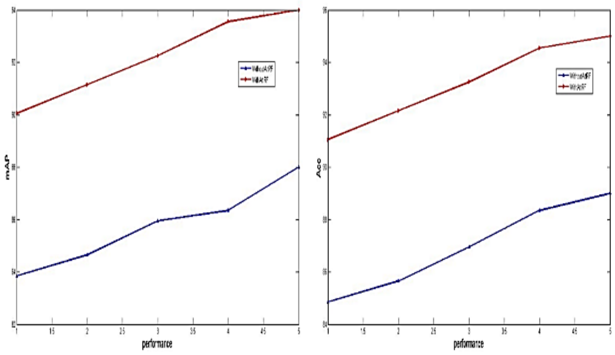

Figure 5. Comparison results of AttRF

In this study, the basic network of the encoder is a Whale Optimized Artificial Neural Network (WO-ANN), and the viability of this network is assessed by comparing it to the VGG network and the INI network. Figure 6 presents the experimental findings. The maximum mAP and accuracy can be obtained by utilizing the WO-ANN network as the encoder's fundamental network, as shown by the data in the figure, which validates the validity of the decision made in this study.

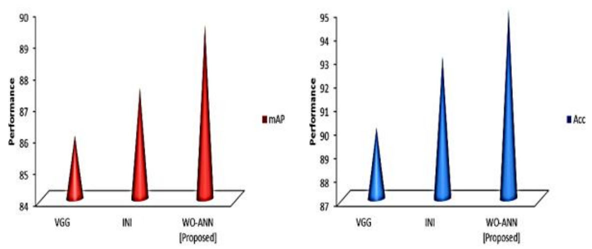

Figure 6. Comparison of different networks

Basketball sports instruction videos are used as an input for this study. The comparison of mAP and accuracy under various frame counts demonstrates the effect of different video frames on performance. Figure 7 presents the experimental findings.

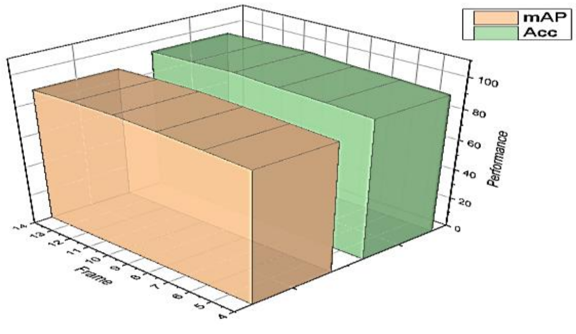

Figure 7. Outcome of different video frame

From figure 7, we can observe that the effects of video frames using CapsNet approach has obtained an accuracy of 98.8% and mAP of 95.5%. It states that the proposed model works well in analyzing the performance of video frames used in basketball training.

5. Conclusion

The wide range of complicated human motions required in basketball makes accurate recognition of these motions crucial for both practice and games. While coaching, a lot of stock is put on the coaches' own personal impressions and anecdotes. Athletes' training might be monitored using tech built on big data and AI. It could also aid coaches in making strategic decisions that have a significant impact on their athletes' performance by analysing their motions. In order to better instruct basketball players, the authors of this study created a method they call ARBIGNet, which uses action recognition. The method employs a Whale Optimized Artificial Neural Network, a network trained with extensive data from basketball games (WO-ANN). In this study, the Convolution Random Forest (ConvRF) unit is initially used to extract spatiotemporal information features of basketball sports training from films. Attention Random Forest (AttRF) unit. It examines each location at random, paying special attention to the areas where action is going place. The network's structure is then developed by upgrading the traditional encoder-decoder paradigm. The video's spatiotemporal data is then encoded using the Enhanced Darknet network model. Experimental testing of the proposed method for improving action identification in basketball sports training has shown a 95.5% mAP and 98.8% accuracy rate. In future work, this method needs to focus on more accuracy with less processing time.

Acknowledgements.

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