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Article

Biomechanical analysis and optimization of sports action training in virtual reality (VR) environment

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Abstract: Over the past years, virtual reality (VR) has become much more popular. VR combines several technologies to provide an immersive digital environment. This environment allows users to engage and react to their actions, creating a virtual world where users feel more present. In biomechanical analysis, researchers analyze the physical characteristics of biological tissues and model the relationship between tissue form and function. Utilizing VR headsets, motion-tracking apparatus, and realistic virtual worlds that simulate actual sports situations are all part of virtual sports training. VR lacks realism, which can be related to the absence of sensory input, making it unsuitable for training fine motor skills. The research aims to perform biomechanical analysis and optimize sports action training inside a VR setting. A mountain gazelle optimizer fine-tuned adjustable convolution neural network (MGO-ACNN) is proposed to examine the joint angle selections utilized by sports action. In this study, human motion image data are utilized to capture various angles of the training action. The data was preprocessed using a Wiener Filter (WF) for the obtained data. Analyzing spatial frequency and orientation in images for feature extraction is accomplished using the Gabor Filter (GF). This approach incorporates VR simulations to provide a more regulated and immersive setting for joint angle analysis during sports training. The proposed method is implemented using Python software. The result demonstrated by the proposed method significantly outperforms the existing algorithms. The performance parameters for accuracy (99.73%), precision (99.75%), recall (99.73%), and F1-score (99.72%) are assessed in this study. The VR experiments indicate that optimal sports preparation involves a sports action while maintaining a batting speed consistent with the joint to lower the center of gravity. This research highlights the more effective, personalized sports training system, leveraging VR to simulate real-world conditions while providing detailed biomechanical insights.

Keywords: biomechanical analysis; sports action; virtual reality (VR); mountain gazelle optimizer fine-tuned adjustable convolution neural network (MGO-ACNN)

1. Introduction

Virtual reality (VR) has shown to be a very helpful tool not only for entertainment but also for a variety of other applications, including training [1], rehabilitation [2], researching human behavior [3], and visualizing [4]. VR is used in various fields to give users a very immersive and entertaining environment in which to observe and interact with the information. Many real-world experiences are being transformed into virtual ones and delivered into peoples' living rooms, attributable to the growing popularity of VR devices and accessories. For certain individuals, using VR for fitness might even have tangible advantages. In particular, people may increase their physical health and fitness while having entertainment by playing and working out at the same time [5]. The musculoskeletal system has a biomechanical load-response pathway that produces mechanobiological tissue reactions in the articular cartilage, bones, tendons, ligaments, and muscles in reaction to frequent, strong treatment. An increasing body of research suggests that tracking the physiological and biomechanical stresses independently can help to provide comprehensive knowledge of the several systems of adaptation that ultimately define a person's degree of performance and physical fitness [6]. The majority of sports action available on the market, whether it's on video or online, shows the sport's movements mechanically and is unable to direct or correct viewers' actual actions. It is generally up to the trainees to truly grasp the fundamentals of tennis because even the occasionally offered on-site training programs by some sports coaches essentially rely on the coach's intuitive experience without imparting sufficient professional knowledge and techniques. Thus, from the standpoint of biomechanics, the process of training athletes has given rise to a contentious debate [7]. Although other sports action training motion sequences like attacking, leaping, and blocking have been studied, the overhead pass motion has not yet been studied, hence the methods used to teach it are not always based on evidence. Players might benefit from theoretical background knowledge that would help them acquire this skillful move if the process of an overhead pass was thoroughly explained [8]. Accurate motion capture and real-time feedback are crucial and limited by the precision of VR sensors and tracking systems. Simulating the physical interaction with the ball's realistic force feedback remains difficult, often affecting player coordination and skill transfer [9].

Moreover, virtual environments lack the fidelity necessary to mimic the spatial dynamics of the real world, leading to discrepancies in movement patterning [10]. Some of the obstacles in the development include user fatigue, hardware limits, and complexity in transcribing 3D biomechanics into a real environment for training. The study aims to improve sports action training in the VR environment and biomechanical analysis is to be carried out. In particular, the study examines the MGO-ACNN study model of preference in play action ring selection ahead in sports action. In the attempt to create a more controlled environment, the research exercise uses data from human motion images and VR simulations to explore and enhance aspects of the joint in sports activities and, consequently, efficiency in the practice of sports.

Contribution of the study

The following are the study's significant contributions.

1) The study introduces a novel method called the mountain gazelle optimizer micro-adjustable convolutional neural network (MGO-ACNN), specifically for analyzing joint angle selection during VR training in sports performance.
2) The study leverages VR tools to provide a more controlled and immersive environment for biomechanical analysis, enhancing the efficiency of sports action training.
3) Preprocessing approach using WF to optimize human motion image data, improving the accuracy of joint angle analysis.
4) The research demonstrates that VR simulations combined with the proposed method provide personalized sports training, offering detailed biomechanical insights for optimized athletic performance.

A summary of the related work is provided in section 2. The dataset, preprocessed data, feature extraction, and classification model are described in section 3. Section 4 presents the instances of experimental setup, comparative study, and overview of study discussion. Section 5 implements the conclusion with limitations and future work.

2. Related work

This section demonstrates the previous research on biomechanical analysis and optimization of sports action training in a VR environment.

An AVR-based rehabilitation system that enhanced patient participation in rehabilitation training by combining upper limb rehabilitation technology with a VR physical training monitoring environment for precise interaction. The system made use of the Convolutional Pose Machine (CPM), a deep learning (DL) motion recognition model that employed a stacked hourglass network [11]. The system was employed in real-time applications because it had an average reaction time of $23\ ms$. To recognize a sportsperson’s activities and motivate someone to become more proficient in sports, a Bio-inspired algorithm (BIA) with long short-term memory networks (LSTM) framework was developed [12]. Comparing the suggested method to other approaches, the experimental findings demonstrated that it was very accurate in assessing athletes’ real actions. The primary problem of sports game identification was accurately tracking athletes’ actions.

Technology that was used to observe and interact with virtual environments was combined to create VR [13]. The 3D space that the atmosphere depicts was imagined, tiny, or macroscopic, and it could be based on real-world or made-up dynamical rules. The study examined the future tendencies of VR in the domains of sports, education, and the military after summarizing the advancements in the technology. It has created a technique for action recognition known as Hierarchical Feature Reduction-Deep Learning (HFR-DL) [14]. Utilizing the UCF101 dataset, which was extensively utilized by action recognition researchers, as a benchmark, they assessed the suggested approach. Comparing the experimental findings with eight approaches, a considerable increase was observed in terms of accuracy and speed.

A machine learning (ML) and image feature extraction approach for basketball shooting gesture identification [15]. To accurately determine the athletic posture of basketball players and enhance their training impact. The evaluation of the shooting action recognition effect and the real case analysis demonstrate the excellence of developed basketball shooting action recognition technology. With the help of a CNN, the human action recognition (HAR) model was created [16] and recognized the present action state by analyzing task action data from collected videos. A HAR algorithm was used to analyze players’ sports psychology and pinpoint the psychology of athletes in their motions. The work used an enhanced convolutional three-dimensional network (C3D) HAR model with an image loss of 5.6 and 80% recognition accuracy. Moreover, there was a 33% decrease in temporal complexity.

To further create a tool to assist athletes’ and trainers’ activities, the current effort attempted to establish the optimal model for screening elite and rookie fencers [17]. It gathered anthropometric and biomechanical data from expert and beginner fencers in a cross-sectional study that was carried out at a fencing club. Biomechanical data was gathered using wearable sensors, such as four surface electromyographic (sEMG) probes and a wireless inertial system. Multilayer Perceptron (MLP) was the best ML method, for class novice (0), its forecasts revealed 90% accuracy, recall, 93% precision, and F1-score, and for class élite (1). The study used every bibliometric approach [18], doing statistical analysis on the state of sports research and the growth pattern of master's including doctorate dissertations. It intended to comprehend the most recent advancements in Chinese sports biomechanics research on martial arts routines. The recall rate was 75.8%, the accuracy of the initial report was only 77.1%, and the F value was 76.3% when using the Naive Bayes (NB) technique.

The Ensemble Neural Network (ENN), a novel model for recognizing sporting events, was created by fusing many networks [19]. The accuracy was at CNN's level of 94.81, above and over 95% of ENN. The measuring system and data collecting platform prototype that was suggested to recognize sports activities were emphasized as having a lot of promise for the privacy-training sports system. The study looks for indicators of muscle injury in professional soccer players by combining biomechanical studies and ML approaches [20]. Advanced models for injury detection and prediction were becoming more and more necessary to help physicians diagnose or identify injuries earlier and more accurately. Among the 35 methods used, extreme gradient boosting (XGBoost) produced an accuracy of up to 78%.

The work was an attempt to achieve similar results by using a single optical sensor to implement several different technologies [21]. The creation and application of a pipeline for extracting monocular features was required to improve the state of the art in sports biomechanics analysis. It would examine the techniques offered and discuss how it has integrated these strategies into the framework. To determine the mechanistic origins of musculoskeletal tissue damage and degeneration, the research investigated the use of biomechanics [22]. It evaluated the application of biomechanics in the creation of training curricula to preserve or regain tissue health.

These innovative methods made 3D body forms, anthropometrics, and kinematics more accessible and useful for a variety of applications by enabling their estimate from as basic as a single-camera image. The system presented [23] in the work combined these approaches with conventional musculoskeletal modeling to allow for the entire investigation of spinal biomechanics during intricate tasks using a single camera.

Research gap

The difficulty addressed in the above research is every challenge of optimizing sports action training within VR environments, particularly for fine motor skills and biomechanical analysis. Traditional VR systems, while providing immersive experiences, often lack the sensory realism required for precise training of sports actions. The limitation affects the effectiveness of VR in simulating real-world sports scenarios and optimizing training methods. The objective is to improve the effectiveness and realism of VR-based sports training with the aid of the integration of biomechanical analysis and sophisticated simulations inside a VR environment. This study specifically addresses the need for a more authentic method for analyzing and optimizing sports actions with MGO-ANN, the novel method. This method involves human motion image data and preprocessing techniques that provide very detailed information on the joint angles as well as movement patterns. The study aims to demonstrate how including these methods in VR results in more personalized and efficient sports training systems and eventually leads to the improvement of athleticism, which is further enhanced by better biomechanical analysis.

3. Methodology

In this section, biomechanical analysis and how to improve sports action training within a VR environment have been clearly explained. **Figure 1** outlines the flow of the proposed methodology framework. At first, human motion image data is collected to serve as the dataset. The data is then preprocessed using a WF to enhance quality. For classification, an MGO-ACNN is employed. The findings are evaluated through simulations, offering a controlled and immersive sitting for joint angle analysis during sports action training.

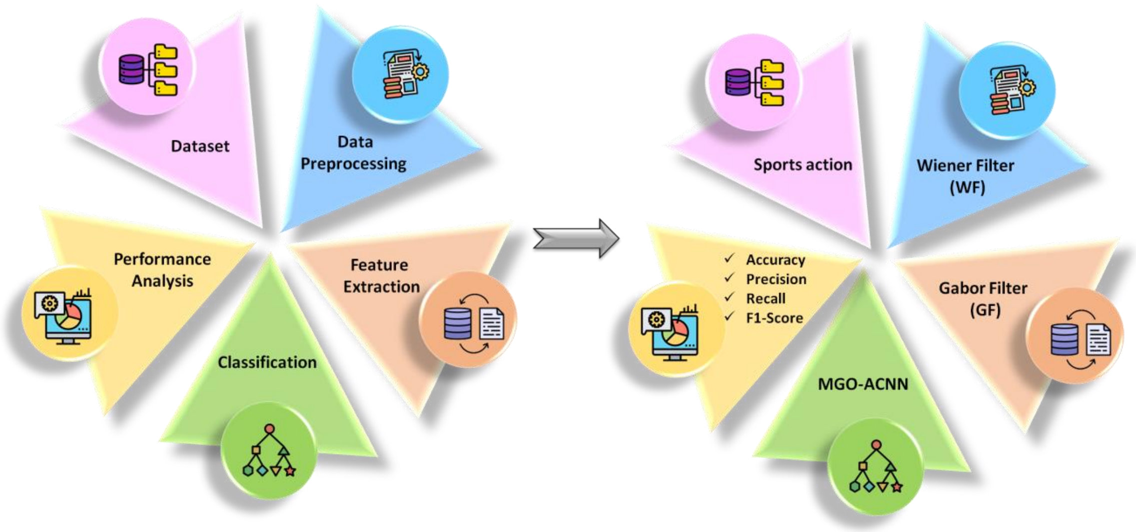

Figure 1. Proposed model.

3.1. Virtual reality

High-resolution cameras or motion-tracking sensors are used to capture images of sports performing action training. It includes recording parts and moves to ensure detailed data is included. By creating simulated environments that closely mimic real situations, including VR, athletes can improve their skills in a safe and fun environment. It improves the training by making it an engaging and enjoyable experience, enhancing the accuracy it offers in comparison to traditional methods. VR enables gamers to visualize and understand complex patterns of movement in 3D space. This type of visualization can help to analyze body mechanics, improve technique, and make adjustments based on real-time feedback. The VR immersive experience (VIVE) is made possible by tracker, a stand-alone headset called Oculus Quest 2 that features a variety of sports training apps and virtual replicas that incorporate this movement into a virtual reality training program. With its precise motion tracking and high-resolution graphics, the high-tech computer corporation (HTC VIVE Pro) is a great choice for comprehensive sports training regimens. Custom

VR training simulations are made with the Unity game development engine. The stereolabs (ZED) stereo camera enhances depth perception and spatial awareness, facilitating movement analysis and skill development, as depicted in **Figure 2**. **Figure 2** illustrates a framework for sports action training within a VR system. The image depicts two individuals engaged in different sports activities: one playing tennis and the other practicing soccer, both wearing VR headsets. This representation emphasizes the immersive and interactive nature of VR technology in enhancing sports training experiences by simulating real-game scenarios.

Figure 2. Framework of spots action training for VR system.

3.2. Dataset

The data was collected from Kaggle [24]. A collection of 1160 films that are divided into 11 different action classes is called the YouTube Action Dataset (UCF11). The dataset is purposefully designed to be difficult due to the wide range of variations in camera motions, object pose and appearance, object scale, perspective, cluttered backdrops, and lighting conditions included in the video clips.

3.3. Data preprocessing using a wiener filter (WF)

The input image $J(m,n)$ is placed through a WF process, which creates the estimate as the result by filtering a known image that is comparable to the input. The goal of this procedure is to construct a statistical estimate of an unknown image. The Gaussian-type additive noise and the blurring are promptly reversed in the WF. To obtain the optimal mean square error (MSE) outcomes, the WF lowers the total mean square error (MSE) during the inverse filtering and noise smoothing procedures. Following Equation (1) preprocessing, every obtained image moves on to the next phase, which involves feature extraction. It is described theoretically as $J(m,n)$ that transforms into $B(v,u)$ using the Discrete Fourier Transform (DFT). Calculating the product of $B(v,u)$and $H(v,u)$ yields an approximated original spectrum. Equation (1) contains the WF is $H(v,u)$, where $G(v,u)$ denotes the point spread function's Fourier transform (FT),$o_t(v,u)$is the signal process's power spectrum, and$O_m(v,u)$is the noise process's spectrum.

$$H(v,u) = \frac{G \times (v,u) o_t(v,u)}{|G(v,u)|^2 o_t(v,u) + O_m(v,u)} \tag{1}$$

3.4. Feature extraction using gabor filter (GF)

The features of GFs, sometimes called Gabor wavelets, are comparable to those of the human visual system, especially in terms of representations of frequency and direction. These are appropriate for discriminating and representing textures. GFs use statistical data on character structures to directly extract features from grayscale images. However, an adaptive sigmoid function is used for the GF outputs to enhance performance on low-quality images. A 2D GF has a spatial response and frequency determined by Equations (2)–(3). It is a complex modulated sinusoidal function of a Gaussian kernel.

$$g(w,z;\lambda,\phi,\sigma,\sigma)=\frac{1}{2\pi\sigma_w\sigma_z}\exp\left\{-\frac{1}{2}\left[\frac{Q_1^2}{\sigma_w^2}+\frac{Q_1^2}{\sigma_z^2}\right]\right\}\times\exp\left[j.\frac{2\pi Q_1}{\lambda}\right] \quad (2)$$

where,

$$Q_1=w\ cos\phi+z\ sin\phi$$

$$Q_2=-w\ sin\phi+z\ cos\phi$$

$$G(v,v;\lambda,\phi,\sigma_w,\sigma_z)=exp\left\{-2\pi^2\left(\sigma_w^2\left(E_1-\frac{1}{\lambda}\right)^2+\sigma_z^2(E_2)^2\right)\right\}\times D \quad (3)$$

where,

$$E_1=v\ cos\phi+u\ sin\phi$$

$$E_2=-w\ sin\phi+z\ cos\phi', D=Constant$$

where, A and B represent the GF’s spatial localization, which is calculated using spatial width as shown in Equation (4).

$$(\Delta w)^2=\frac{\int_{-\infty}^{+\infty}gg^{\times}(Q_1)^2c(Q_1)}{\int_{-\infty}^{+\infty}gg^{\times}c\ (Q_1)} \quad (4)$$

3.5. Classification using mountain gazelle optimizer fine-tuned adjustable convolution neural network (MGO-ACNN)

To adjust the search strategy provided, MGO-ACNN utilizes sophisticated techniques for performance improvement. The acronym MGO describes the adaptive feeding behavior of gazelles or the optimization of the hyperparameter of ACNN to gain better accuracy in the classification of entities. Optimizing simple parameters such as the learning rate and filter sizes significantly enhances the ability of ACNN to detect complex patterns in data. The changeable part of ACNN dynamically adjusts its structure according to the optimization result to extract features and classify them accurately. Therefore, MGO and ACNN put together a very robust and efficient classification algorithm that can be used to classify complex datasets with accuracy and efficiency.

3.5.1. Adjustable convolution neural network (ACNN)

Sport function training using ACNN is to increase the accuracy and adaptability of movement assessment by adjusting the amount of variables in intensity to capture the objective of improving performance outcomes through information on the delivery of authentic and personalized delivery to enhance the quality of training programs. The ACNN model's convolution layer, which is the first layer, pulls characteristics like edges and textures from the input image of sports action. This layer moves the extracted output to the next layer inside the model after applying a convolution operation on the input sports action image. To get an output in the form of a feature map, the convolutional layer receives a three-dimensional input in terms of height, width, and channel count. Additionally, the rectifier linear unit (ReLU) is included in the activation function (AF) of the convolutional layer. As a result, the ACNN model gains non-linearity and the convolution layer can keep only positive input. Feature maps are the input of a pooling layer, a down-sampling layer that is often applied after the convolution layer. Applying pooling layers is mostly done to reduce the feature maps' spatial resolution. By gradually shrinking the spatial size of the feature maps, max pooling was used to lower the network's computation and parameter count, as shown in **Figure 3**.

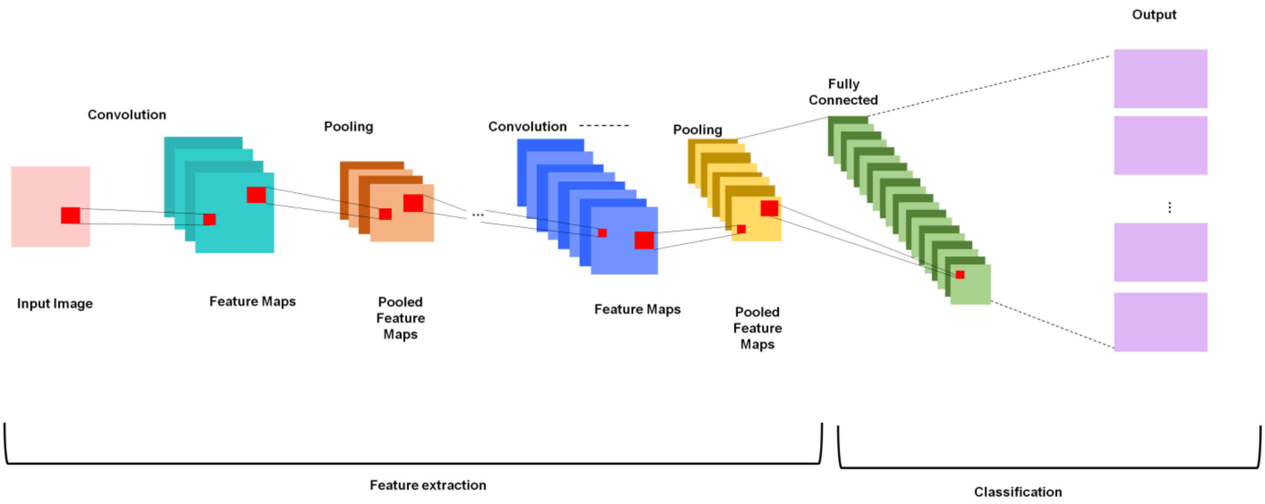

Figure 3. Architecture of ACNN.

To extract features, several flattened layers and convolutional pooling layers are used in conjunction. The rationale and feature representations are deduced by the thick layer that follows these layers. An activation function called Softmax is utilized in ACNN's output layer. ACNN's output layer uses Softmax because it offers the probability distribution across the classes needed to classify the input image, while the fully connected layer is free to employ any kind of activation function. The Softmax function outputs a vector with a list of possible outcomes that match the probability distribution. The input vector is denoted by z_j in Equation (5), T is softmax, and f^{z_j} is a conventional exponential function of an input function.

$$T(z_j) = \frac{f^{z_j}}{\sum_i f^{z_j}} \tag{5}$$

For every image, there are exactly as many neurons in an output layer as there are classes that need to be identified for sports action. With the image belonging to the class with a high likelihood, each neuron in the output layer displays the probability distribution of the image for each class.

3.5.2. Mountain gazelle optimizer (MGO)

MGO exists to enhance athletic performance by optimizing training techniques and strategies through advanced algorithmic models. MGO optimizes training simulations to improve overall performance, speed, and efficiency. The MGO is a recently developed meta-heuristic algorithm that predicts how mountain deer behave in groups and their natural environments. Four main facets of mountain gazelle life serve as the foundation for the optimization operations of the MGO algorithm, such as maternity herds (MH), migration-quest of food (MSF), bachelor male herds (BMH), and territorial solitary males (TSM). **Figure 4** gives an illustration of the techniques used by MGO to carry out optimization operations, and the following sections provide a mathematical description of those strategies.

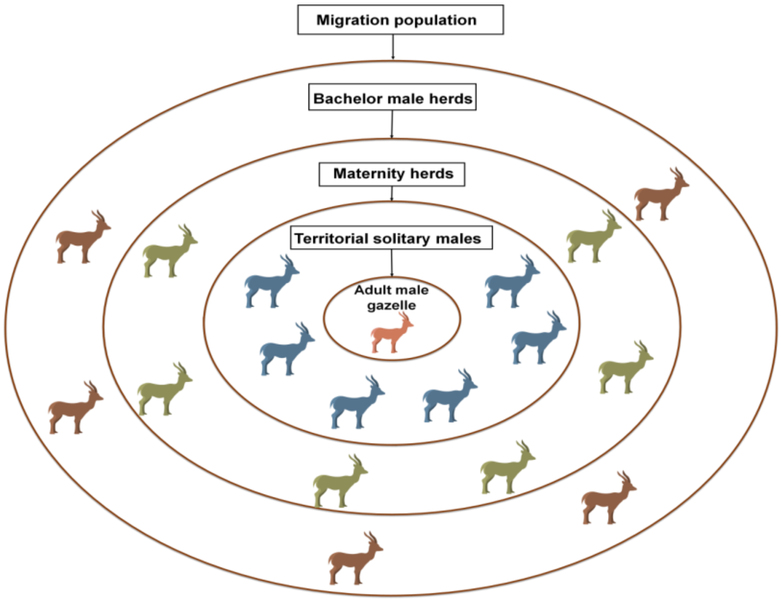

Figure 4. Framework of MGO algorithm.

TSM

When male gazelles mature and become capable of self-defense through physical means, individuals keep separate, highly secure territories that are easily identifiable by distance. To gain possession of the female's territory, adult male gazelles engage in combat with one another. The goal of mature males is to defend their environment, whereas teenage males want to take control of the female area. The domain of an adult man is depicted in Equations (6)–(10).

$$TSM = male_{gazelle} - |\beta_1 \times AG - \beta_2 \times W(s) \times E| \times Cof_q \tag{6}$$

$$AG = W_{qb} \times [q_1] + N_{oq} \times [q_2], qb = \{\left\lceil \frac{M}{3} \right\rceil \dots M\} \tag{7}$$

$$E = M_1(C) \times exp(2 - js \times \left(\frac{2}{Maxit}\right)) \tag{8}$$

$$Cof_q = \begin{cases} (b+1) + q_3 \\ b \times M_2(C) \\ q_4(C) \\ M_3(C) \times M_4(C)^2 \times cos(2q)_4 M_3(C) \end{cases} \quad (9)$$

$$b = 1 + js \times \frac{-1}{Maxit} \quad (10)$$

where $male_{gazelle}$ stands for the best adult male position vector. $W(s)$ is the gazelle 's starting position. The random integers β_1 and β_2 have values of either 1 or 2. The young male herd's coefficient vector is designated as AG. To increase the search region's efficacy, Cof_q is an additional randomly produced coefficient vector that is modified after each iteration. W_{qb} is a young boy within the range of N_{oq}, and qb is the standard number of populations $\left[\frac{M}{3}\right]$ that were chosen at arbitrary. M represents the whole population of gazelles, whereas the designations q_1, q_2, q_3, and q_4 are arbitrary numbers between 0 and 1. M_1 denotes the random number selected from the normal distribution. M_2, M_3, and M_4 describe the issue's dimensions and the arbitrary integers in the normal range. The exponential function is represented by exp, whereas the cosine function is represented by cos. Lastly, $Maxit$ and js represent the current generation and the maximum number of generations, respectively.

MH

The production of healthy male offspring is an essential aspect of the life cycle of maternity-herd-dependent mountain gazelle species. Male gazelles have been known to assist in gazelle birthing besides aiding young males who are attempting to lust for women. This behavior is described by Equation (11).

$$NG = \left(AG + Cof_{1,q}\right) + \left(\beta_3 \times male_{gazelle} - \beta_4 \times w_{rand}\right) \times Cof_{2,q} \quad (11)$$

where arbitrary integers 1 or 2 are indicated by β_3 and β_4. The entire population is chosen at random to include one gazelle, and w_{rand} represents its vector location. The randomly selected coefficient vectors are $Cof_{1,q}$, and $Cof_{2,q}$.

BMH

To grow older, male gazelles typically establish territories and demonstrate their dominance over females. Currently, older males and young male gazelles are battling for control over females, perhaps leading to violent altercations. Equations (12) and (13) provide a mathematical expression for this phenomenon.

$$BMH = (W(s) - C) + (\beta_5 \times male_{gazelle} - \beta_6 \times AG) Cof_q \quad (12)$$

$$C = \left(|W(s)| + \left|male_{gazelle}\right|\right) \times (2 \times q_6 - 1) \quad (13)$$

The symbol $W(s)$ represents the current iteration's gazelle's vector position. The random numbers, β_5 and β_6, are selected between 1 and 2. The random number, which goes from 0 to 1, is q_6.

MSF

When seeking food, mountains, and gazelles cover a lot of ground and never stop searching for fresh supplies. Conversely, mountain gazelles possess a strong bounce force and a swift gait. When looking for food and migrating, mountain gazelles often travel great distances. The following Equation (14) provides a mathematical expression for this phenomenon.

$$MSF = L + (U - L) \times r_7 \tag{14}$$

where an arbitrary integer between 0 and 1 is implied by r_7. The upper and lower boundaries are shown by U and L, respectively. Algorithm 1 depicts the classification model of MGO-ACNN.

Algorithm 1 Mountain gazelle optimizer fine-tuned adjustable convolution neural network (MGO-ACNN)

Input: Initialize parameters
Step 1: Function evaluateACNN(gazelle_position):
ACNNParameters($gazelle\_position$)
TrainACNN()
    accuracy = TestACNN()
return accuracy
Step 2: For iteration from 1 to Maxit:
$TSM\_update = UpdateTSM(gazelle.position)$
$MH\_update = UpdateMH(gazelle.position)$
$BMH\_update = UpdateBMH(gazelle.position)$
$MSF\_update = UpdateMSF(gazelle.position)$
Step 3: Compute new position
$gazelle\_new\_position = TSM\_update + MH\_update + BMH\_update + MSF\_update$
Step 4: Evaluate new ACNN configuration
$gazelle\_new\_accuracy = evaluate\ ACNN(gazelle\_new\_position)$
Step 5: Update gazelle position if new accuracy is better
if$gazelle\_new\_accuracy > gazelle.best\_accuracy$:
$gazelle.position = gazelle\_new\_position$
$gazelle.best\_accuracy = gazelle\_new\_accuracy$
Step 6: Output the best configuration and performance
$best\_gazelle = FindBestGazelle()$
Print("Best ACNN Configuration: ", best_gazelle.position)
Print(Best Accuracy:best_gazelle.best_accuracy)
Step 7: Function UpdateTSM(position):
    Implementation based on equations (1-5)
return $updated\_position$
Step 8: Function UpdateMH(position):
    Implementation based on equation (6)
return$updated_position$
Step 9: Function UpdateBMH(position):
    Implementation based on equations (7-8)
return$updated_position$
Step 10: Function UpdateMSF(position):
    Implementation based on equation (9)
return $updated\_position$
end

4. Result and discussion

In this section, the initial phase provides setting up and configuring the techniques to ensure the components are properly integrated and functioning according to the specifications. It is crucial to establish a solid foundation for accurate and reliable results. Next, the following system configuration is to conduct a thorough comparative analysis. This involves evaluating and contrasting the performance, effectiveness, and other relevant metrics of different systems of methodologies.

4.1. System configuration

The experimental environment is configured with a Windows 7 operating system, an Intel i7-7700 CPU, a GeForce GTX 960 GPU, 16 GB of RAM, and 512 GB of storage. The receiver devices used are HUAWEI WATCH 1 and HUAWEI Nexus 6P. Software used included Python libraries such as OpenCV, TensorFlow, and Keras to implement keypoint detection and pose estimation algorithms. These libraries offer graphics services and deep learning tools that are integrated into VR training programs. Ensure that the keypoint detection system is properly integrated with the VR environment to enable real-time tracking and analysis during training.

4.2. Comparative analysis

With the use of reconstructed key point attributes, compare the effectiveness of the proposed MGO-ACNN approach with the existing algorithms such as the Dynamic Bayesian mixture model (DBMM) [25], and CNN-Weighted Error-correcting output codes (CNN-WECOC) [26]. Assess metrics such as recall, accuracy, precision, F1-score, and the effectiveness of joint angle optimization.

Accuracy: It is a quantifiable measure of prediction correctness in sports action. The total number of correct predictions a model makes is determined using the evaluation metric known as accuracy. A model’s accuracy is a statistic that expresses how frequently it predicts an outcome accurately of sports action, as following Equation (15).

$$\text{Accuracy} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{15}$$

True positives are represented by TP, false positives by FP, true negatives by TN, and false negatives by FN, and are stated in Equations (15)–(18).

TP: In terms of forecasts made correctly, TP stands for positive predictions.

FP: FP stands for the wrongly predicted class’s negative predictions.

TN: TN is a representation of a successfully predicted class’s negative predictions.

FN: The positive expectations of an improperly predicted class are represented by FN.

Table 1 shows the accuracy of existing and proposed methods for motion recognition. The DBMM method achieved an accuracy of 96.47%, while the CNN+WECOC approach performed better, with 99.71% accuracy. The suggested model slightly outperforms MGO-ACNN, achieving the highest accuracy of 99.73%. This slight but significant improvement highlights the usefulness of the suggested method in contrast to alternative approaches and highlights its potential for increased task accuracy. Overall, the findings show that the suggested approach offers little improvement over the current model. **Figure 5** gives the graphical representation of the accuracy result of the proposed model compared with the existing techniques.

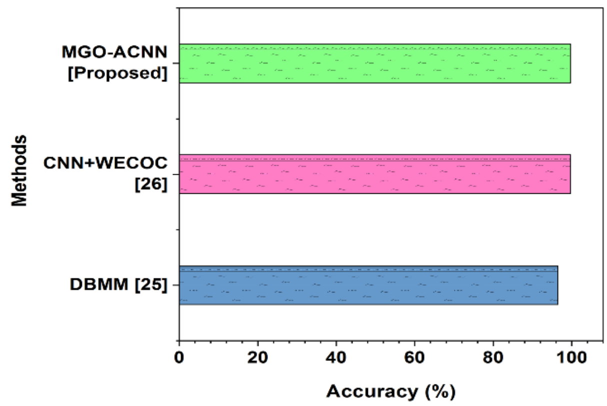

Figure 5. Comparative analysis of accuracy.

Table 1. Numerical outcomes of accuracy.

Methods	Accuracy (%)
DBMM [25]	96.47
CNN+WECOC [26]	99.71
MGO-ACNN [Proposed]	99.73

Precision: A classifier's precision is measured by sports action by calculating the percentage of positively labeled tuples that are truly positive. Precision is utilized to ascertain the proportion of characteristics of a given class that were correctly and mistakenly assigned, while measurements with a wide variety of applications, such as recall and F1-score, are also used, as following Equation (16).

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{16}$$

Table 2 shows the precision rates of the existing and proposed methods. DBMM achieved a lower precision of 77.70%, indicating a relatively high false-positive rate, likely due to its challenges in handling complex sports actions. The CNN+WECOC method performed significantly better, achieving a precision of 99.72%, which shows its ability to correctly classify true positives with fewer false positives. The proposed MGO-ACNN model reached a precision of 99.75%, marking a marginal but critical improvement, highlighting its more refined classification process, thanks to the integration of the optimization technique. This comparison is also represented graphically in **Figure 6**.

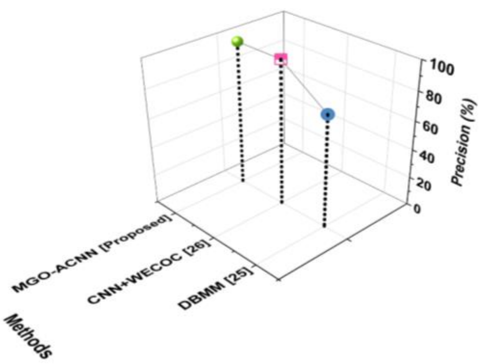

Figure 6. Comparison of precision.

Table 2. Outcomes of existing and proposed approach.

Methods	Precision (%)
DBMM [25]	77.70
CNN+WECOC [26]	99.72
MGO-ACNN [Proposed]	99.75

Recall: Conversely, recall quantifies completeness and shows the proportion of accurately labeled true positive pairs. For unbalanced datasets, accuracy by itself is not a suitable criterion for evaluation. It's the ratio of accurately anticipated positives to the total number of positive observations, as following Equation (17).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{17}$$

Table 3 and **Figure 7** show the recall percentages of existing and proposed methods. The DBMM method achieved a recall of 84.12%, indicating s fair capability to detect true positives but missing a notable percentage. The CNN+WECOC method significantly improved recall to 99.71%, showcasing a high level of accuracy in capturing the true positives. The proposed method achieved a recall of 99.73%, slightly higher than CNN+WECOC, showing that it further improved the completeness of positive case identification, particularly in dynamic, real-time VR-sports action analysis.

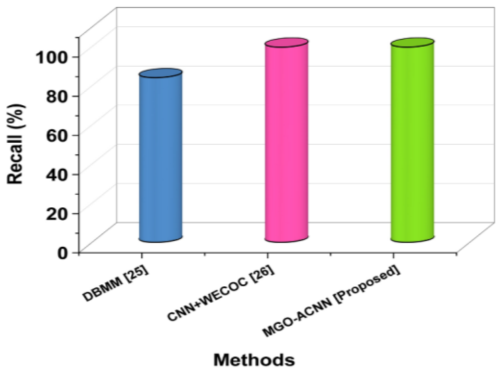

Figure 7. Comparison of recall.

Table 3. Numerical outcomes of existing and proposed approach.

Methods	Recall (%)
DBMM [25]	84.12
CNN+WECOC [26]	99.71
MGO-ACNN [Proposed]	99.73

F1-score: It is the harmonic average of recall and accuracy, that is useful in these circumstances. To consider the model's recall and precision, it applies statistical analysis to get a score between 1 and 0.

$$\text{F1 score} = 2 \times \frac{\text{precision.recall}}{\text{precision} + \text{recall}} \tag{18}$$

Table 4 and **Figure 8** demonstrate the F1 scores which is crucial for understanding the model's overall effectiveness in classification. DBMM scored 80.54% showing moderate performance due to its lower precision and recall. The CNN+WECOC method showed a significantly higher F1-score of 99.70%, reflecting its superior ability to accurately classify data. The proposed method slightly outperformed, achieving an F1-score of 99.72%, emphasizing its superior balance of accuracy, precision, and recall. This improvement, while slight, is significant in high-performance applications like VR-sports training.

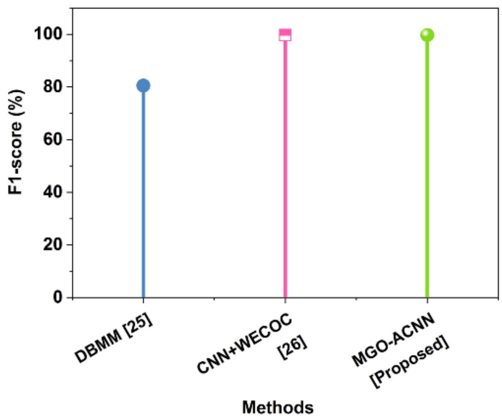

Figure 8. Comparative analysis of F1-score.

Table 4. Numerical outcomes of existing and proposed model.

Methods	F1-score (%)
DBMM [25]	80.54
CNN+WECOC [26]	99.70
MGO-ACNN [Proposed]	99.72

4.3. Study discussion

In this study, the performance of the proposed MGO-ACNN method is evaluated against established algorithms, DBMM and CNN-WECOC. The results detailed in **Tables 2–4** and **Figures 4–7** demonstrate the MGO-ACNN consistently outperforms the other methods across various metrics. A scientific approach called biomechanical analysis examines how people move in sports to enhance performance and lower injury risk. To comprehend how the body reacts to outside influences entails examining the motion, forces, and equipment interactions of the body. When attempting to differentiate between several classes in images, when differences and similarities among them might make it difficult, WECOC has been utilized extensively. The problems of employing CNNs include object identification, picture categorization, object location, and image annotation. The primary drawbacks of CNNs are that they take a lot of training information and computer resources to train, and are typically difficult to align. The existing methods exhibit several limitations in the context of sports action training in VR. CNN-WECOC suffers from issues related to overfitting lower generalization when handling complex motion data, as it struggles to accurately capture the fine variations in joint angles during dynamic sports activities.

Additionally, CNN-WECOC's classification performance is limited in high-variable training scenarios due to its static nature in adapting to diverse movement patterns. DBMM, while effective in probabilistic motion prediction tends to be computationally intensive and lacks real-time adaptability, making it less suitable for real-time VR training environments. In assessment, the proposed approach addresses those shortcomings by incorporating a more adaptive optimization mechanism that complements joint perspective evaluation. The MGO allows for exceptional tuning of the network, improving its capability to deal with complicated spatial versions and dynamic motion. Furthermore, the combination of Gabor filtering for spatial frequency analysis complements characteristic extraction resulting in superior performance. The outcomes show that the MGO-ACNN approach affords small improvement however is significant to the prevailing version. It offers excessive accuracy and an F1 score. Sports biomechanics is the complete study of sports activities moves to reduce the hazard of damage and improve athletic overall performance. Human kinematics is a scientific area involved with the biomechanics of sports and exercise. It improves typical health, reduces the risk of injury, and improves sports activities' overall performance. Biomechanical analysis may additionally help athletes of all ages and talents, either for rehabilitation or to improve overall performance. These upgrades reveal the potential of the MGO-ACNN method to provide higher type performance and reliability in applications that require high accuracy and performance.

5. Conclusion

The study highlights the significant role of incorporating VR into biomechanical analysis for enhancing sports training by providing an immersive real-world-like environment. The proposed MGO-ACNN algorithm offers a groundbreaking approach to analyzing joint angles used in sports action training. By integrating VR simulation, the research provided a controlled, interventional environment that improves the accuracy of joint anterior examination compared to traditional methods. Moreover, by combining VR with advanced imaging techniques such as the WF and GF, the suggested method enables precise extraction and analysis of motion data. The study's findings showcasing superior performance in terms of recall (99.73%), accuracy (99.73%), precision (99.75%), and F1-score (99.72%) underscore the significance of this research. The results demonstrate the potential of VR-based systems to create highly personalized, detailed training experiences that closely mimic real-world conditions, offering valuable insights into optimizing sports performance and refining training methods.

Limitation and future scope

VR simulations lack the sensory statistics important to educate high-quality motor abilities that can lessen the general realism of the training experience. The findings are primarily based on sports activity and won't be without delay relevant to other industries without similarly validation. Future studies specialize in incorporating new sensory factors into VR simulations to enhance the realism and effectiveness of satisfactory motor talents training. Explore advances in VR and motion-tracking technology to make biomechanical evaluation extra accurate and dependable.

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