Journal of Environmental & Earth Sciences
https://journals.bilpubgroup.com/index.php/jees

ARTICLE

Solar-Powered Aerobics Training Robot with Adaptive Energy Management for Improved Environmental Sustainability

Bevl Naidu [1,], Krishna Babu Sambaru [2], Guru Prasad Pasumarthi [3], Romala Vijaya Srinivas [4], K. Srinivasa Krishna [5], V. Purna Kumari Pechetty [6]*

[1] *Department of Management Studies, Aditya Degree & PG Colleges, Andhra Pradesh 533001, India*

[2] *Department of Digital Marketing, Aditya Degree & PG College , Kakinada, Andhra Pradesh 533001, India*

[3] *Department of Research and Analytics, PB Siddhartha Arts and Science College, Vijayawada, Andhra Pradesh 521108, India*

[4] *Department of Research and Analytics, Business School, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, A.P 522302, India*

[5] *Department of Management Studies, Madanapalle Institute of Technology and Science, Madanapalle, Annamayya District 517325, India*

[6] *Department of Research and Analytics, SR University, Anantha Sagar, Hasanparthy, Hanamkonnda 506371, India*

ABSTRACT

With the rapid advancement of robotics and Artificial Intelligence (AI), aerobics training companion robots now support eco-friendly fitness by reducing reliance on nonrenewable energy. This study presents a solar-powered aerobics training robot featuring an adaptive energy management system designed for sustainability and efficiency. The robot integrates machine vision with an enhanced Dynamic Cheetah Optimizer and Bayesian Neural Network (DynCO-BNN) to enable precise exercise monitoring and real-time feedback. Solar tracking technology ensures optimal energy absorption, while a microcontroller-based regulator manages power distribution and robotic movement. Dual-battery switching ensures uninterrupted operation, aided by light and I/V sensors for energy optimization. Using the INSIGHT-LME IMU dataset,

*CORRESPONDING AUTHOR:
Bevl Naidu, Department of Management Studies, Aditya Degree & PG Colleges, Andhra Pradesh 533001, India Email Id: naidubevl@aditya.ac.in

ARTICLE INFO
Received: 8 March 2025 | Revised: 7 May 2025 | Accepted: 21 May 2025 | Published Online: 14 June 2025
DOI: https://doi.org/10.30564/jees.v7i6.9012

CITATION
Lastname, The initials of the firstname., Lastname, The initials of the firstname., Lastname, The initials of the firstname., et al., 2025. Solar-Powered Aerobics Training Robot with Adaptive Energy Management for Improved Environmental Sustainability. Journal of Environmental & Earth Sciences. 7(6): 482–496. DOI: https://doi.org/10.30564/jees.v7i6.9012

which includes motion data from 76 individuals performing Local Muscular Endurance (LME) exercises, the system detects activities, counts repetitions, and recognizes human movements. To minimize energy use during data processing, Min-Max normalization and two-dimensional Discrete Fourier Transform (2D-DFT) are applied, boosting computational efficiency. The robot accurately identifies upper and lower limb movements, delivering effective exercise guidance. The DynCO-BNN model achieved a high tracking accuracy of 96.8%. Results confirm improved solar utilization, ecological sustainability, and reduced dependence on fossil fuels—positioning the robot as a smart, energy-efficient solution for next-generation fitness technology.

Keywords: Aerobics Training Robot; Energy Power Supply Control; Dynamic Cheetah Optimizer (DynCO); Bayesian Neural Network (BNN); Motion Recognition

1. Introduction

Robotics has transformed several activities in uncharted or hazardous situations, including intelligence, surveillance, reconnaissance, and disaster monitoring. Robots must develop more effective energy management techniques and efficiency as missions get more complicated to prolong mission durations. Unmanned Aerial Vehicles (UAVs) need to be both environmentally friendly and economically viable to be considered sustainable. To ensure that these cars are developed and implemented without squandering resources for future generations, this entails deploying robots with a lower environmental impact [1]. The increasing focus on health and physical well-being has highlighted the significance of exercise. Aerobics, a dynamic combination of movement and musical rhythm, draws a wide spectrum of participants, as well as those who are absorbed in dance, fitness, and coordination training [2]. With the quick advancement of computer intelligent vision technology, aerobics continuous image recognition involved in determining aerobics movement. Classical approaches like geometric regularity contour restoration and arithmetic features based on structures were utilized for strengthening aerobics movement analysis with an intention to the enlarged signal-to-noise ratio of the reassembled image [3]. The combination of robotics and Artificial Intelligence (AI) has recently transformed several industries, including sports and fitness instruction. The development of aerobics training companion robots, which offer users cooperating and flexible training experiences, has drawn a lot of attention among these advancements [4]. Machine vision expertise is used by these robots to assess human movements, provide real-time feedback, and growth training effectiveness [5]. Solar UAVs' Energy Management Systems (EMS) must balance energy generation, storage, and consumption while reacting to ambient factors like as daylight temperature and light levels. Improving EMS is critical for collective the speed of flight and sustaining consistent operation [6]. Advanced image processing techniques allow these robots to track body movement, estimate situation, and offer remedial input [7]. To increase user involvement, this real-time feedback organization lowers the chance of harm. Nevertheless, a considerable quantity of energy is consumed by the continuous technique of machine vision apparatus, such as cameras and image processors. Consequently, it is essential to install a smart power organization arrangement to guarantee effective energy use without sacrificing robot performance [8].

1.1. Objective of the Research

The research's foremost intent is to create an energy-efficient power management system for an aerobics training partner robot by combining solar energy with machine vision-based movement analysis. The system is made to function in a assortment of environmental surroundings, assuring continuous process with decreased energy waste. By utilizing the DynCO-BNN, the model enhances motion recognition while maximizing power usage. The adaptive energy distribution mechanism allows real-time tracking of upper and lower limb actions, ensuring precise exercise supervision and response. A key emphasis of the investigation is to create an environmentally sustainable solution by reducing dependency on conventional power sources. The incorporation of solar energy minimizes the carbon footprint, making the system eco-friendlier. Additionally, the model is considered to adapt to environmental variations, maintaining efficiency under different lighting conditions. Ultimately, this research contributes to the development of intelligent fitness robots that operate efficiently while promoting environmental sustainability.

1.2. Key Contribution of the Research

✓ This research describes an innovative aerobics companion robot powered by solar energy and loaded with an adaptive energy management system, which reduces dependency on non-renewable energy sources and promotes environmentally responsible exercise solutions.

✓ Designed an environmentally responsive adaptive tracking system that maximizes solar energy absorption and optimizes power distribution, ensuring sustainable energy utilization.

✓ The research utilizes the INSIGHT-LME IMU dataset, which includes 76 individuals, to identify exercises, estimate recurrence and HAR reliably.

✓ The research employs Min-Max normalization and two-dimensional Discrete Fourier Transform (2D-DFT) to optimize data processing, reducing computational load and unnecessary energy consumption.

✓ The article provides a DynCO-BNN-based motion tracking framework that combines robotic vision and optimizations to recognize limb movements in real-time in a powered by solar energy aerobics training robots.

✓ The suggested technique, DynCO-BNN, is used to improve the reliability of real-time movement identification and observations, resulting in high tracking accuracy.

The rest of the research is followed by: Section 2 provides the related works; Section 3 explains the methodology; Section 4 gives the results; Section 5 and 6 provide the discussion and conclusion.

2. Related works

Yihan (2024) provided an exercise movement identification system that employs biotechnology data and Deep Learning (DL) algorithms [9]. Biosensing technologies and wearable devices are used to acquire real-time physiological signal data from anatomical parts of athletes. Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) are employed, with the model's efficiency improved via parameter selection and techniques. Model C has an accuracy of 0.987, dispatching both standalone CNNs and Recurrent Neural Network (RNN) models. The system also performs efficiently, with decreased execution times for data processing, feature extraction, and classification. Joshi et al. (2024) described the Internet of Things (IoT) devices demand a scarce amount of energy [10], thus it is critical to maintain continuous power supply and communication. A strategy is suggested to provide wireless power as well as data transfer for IoT devices by absorbing solar energy and employing UAV and Reconfigurable Intelligent Surfaces (RIS). The intention is to improve energy efficiency by scheduling IoTUnits (U) energy harvesting and optimizing the UAV orientation. A multi-agent federated reinforcement learning technique is presented, which achieves 96.3% and 97.5% accuracy for interaction circuits and RIS components, respectively, while also improving energy consumption.

Agarwal et al. (2024) established solar-powered cold storage units for street sellers, which provide a dependable and portable alternative in off-grid locations [11]. The technology incorporates solar energy, resulting in flexibility, mobility, and effectiveness. It has an accessible user interface, effective cooling methods, and real-time monitoring via IoT. The system's mobility and IoT integration provide optimal performance and energy efficiency, increasing product quality and shelf life, and ultimately improving corporate operations and profitability. Hazare et al. (2024) suggested an innovative approach for improving solar-powered UAVs utilizing slime mold neural networks for azimuthal solar synchronization and aerodynamic neuro-optimization [12]. The objective is to enhance the endurance and environmental resistance of UAVs so that they can potentially utilized for a variety of tasks such as environmental monitoring and rescue efforts. This technique demonstrates the value of combining biomimicry and neural network-based optimization.

Prauzek et al. (2024) investigated the use of Genetic Programming (GP) and fuzzy logic to enhance the control techniques for IoT nodes [13]. It presents a innovative approach to constructing a fuzzy-based energy management controller that illustrates the ideal regulator architecture and parameters on its own. The technique is examined with a sunlight-generating IoT approach, proving its suitability for a wide range of geographic operations as well as compatibility with low-performance microcontrollers. The investigation established that the model effectively leverages historical records to offer optimal control techniques, with gradual advancement throughout the learning period.

Shao et al. (2023) described a long-term human-robot interaction conducted at a nearby long-term care facility, examining the advantages of workout encounters between older persons and an autonomous socially helpful robot, both individually and in groups [14]. The robot employed a special emotion model to modify its actions and monitor users' progress toward fitness objectives. In one-on-one sessions, consumers valued the robot's intelligence, sociability, and looks, indicating positive valence and high engagement. Mekruksavanich and Jitpattanakul (2024) employed a new DL model to recognize gym exercise activities with wearable sensors directly [15]. Model-recognized exercises with multimodal sensor information using DL models. The model was evaluated with the Myogym dataset based on an F1-score of 92.68% and a classification accuracy of 97.29%. Ablation experiments confirm the effectiveness of the model and demonstrate its capability for personalized training and rehabilitation.

Giordano et al. (2023) investigated how soft robotics might be used to improve environmental sustainability. Investigating biodegradable materials, integrating renewable energy sources, and the difficulties of large-scale maintainable manufacture were all covered [16]. Field-ready soft robots were presented that assist the Sustainable Development Goals (SDGs) in the ranges of urban farming, health care, disaster relief, land and ocean protection, and sustainable energy. This approach encourages clean energy, sustainable manufacturing, financial expansion, ecological preservation, and general health.

Liu et al. (2024) described how industrial robots affect the environment in 10 of the top AI countries between 2007 and 2020 [17]. A Quantile-on-Quantile methodology was determined, which concluded that manufacturing robots enhance environmental quality by reducing their ecological effect. The consequences, showed that variables vary from nation to nation, highlighting the necessity for authorities to closely oversee industrial robots and ecological footprint initiatives. Environmental psychology examined how people behave about their surroundings and how psychological strategies can encourage behavior modification. Wasim et al. (2024) provided an energy management approach for a powered by solar energy battery-ultracapacitor hybrid system that uses a Rule-Based Grasshopper Optimization Algorithm (RB-GOA). The method obtained to correspond with the pulsed load requires extracting the most energy from the solar array [18]. The GOA randomly assigns power shares based on Photovoltaic (PV) battery bank, and ultracapacitor restrictions. The investigation corresponded with the suggested approach to various swarm intelligence systems, and found that it outperformed others in terms of power surge reduction, oscillation mitigation, and Maximum Power Point (MPP) tracking. It lowers power surge by 26%, 22%, and 8% for variable PV with constant load.

Wang (2025) created a fine motion capture and action recognition model for collegiate aerobics instruction that addressed noise and incompleteness concerns [19]. The model's greatest attributes include a 36.5% increase in efficiency for the process captures model and a 59.4% top-up accuracy for the action recognition model. On both datasets, the model exceeded the control group by 9.4 points in terms of classification precision. This increased the ability to impart the efficacy of efficient aerobics training. Ishaya et al. (2025) described IoT which is revolutionizing smart cities by enhancing connectivity and automation [20]. However, questions regarding energy usage, device longevity, and network sustainability have emerged. Energy-efficient protocols, including dynamic power regulation, cycling function, and hybrid energy harvesting, are critical for managing power usage while preserving network dependability. Advanced Medium Access Control and routing protocols, as well as new communication standards, all contribute to reducing energy waste. The research assessed advanced energy-efficient IoT protocols in smart urban environments, with an emphasis on AI-powered energy management, edge computing, and energy-harvesting IoT devices.

Kalbande et al. (2024) appeared at the incorporation of ternary nano-enhanced materials into organic Phase Change Materials (PCM), with Erythritol as the fundamental PCM [21]. Three distinctive nano-enhanced phase change materials are produced by combining nanomaterials and carbon nanotubes. The thermal performance of mono, binary, and ternary nano-enhanced PCM-based thermal energy storage devices is compared with that of the basic PCM. In comparison to traditional systems, ternary nanocomposite nano-enhanced PCM has the best thermal efficiency and power retention capability.Damien Bouchabou et al. (2021) present recent algorithms, works, challenges, and taxonomy of the field of human activity recognition in a smart home through ambient sensors[22].

2.1. Research Gap

Prior work has focused on energy-efficient IoT devices, solar-powered UAVs, and wearable sensors for detecting human activity. However, there is an absence of integrated systems that combine real-time aerobics training coaching, energy efficiency via solar processing, and intelligence motion monitoring with powerful optimization processes in a single robotic framework. Most systems lack an exhaustive solar-adaptive energy management system or use Machine Learning (ML) and AI.

DynCO-BNN covers the loopholes with a blend of optimized feature learning, recognition that is aware of uncertainty, and low-power computation. Different from the typical CNN-based architectures, it conserves computation with no compromise in accuracy to enable real-time response and motion adjustment. With an incorporated solar-driven energy management unit, operation sustainability is assured without much reliance on external power inputs. Furthermore, with an adaptive dual-battery power storage method, efficient consumption of power provides enhanced operation endurance. Through the use of machine vision, the model improves movement accuracy and lessens computationally expensive calculations. Its support for wearable and autonomous robotic systems enables it to be a scalable option for various training environments. With these improvements, the proposed solution offers an overall, eco-friendly, and smart solution for next-generation aerobics training robots.

3. Methodology

Research provides real-time physical activity assessment while reducing dependency on nonrenewable energy and improving ecological sustainability. The solar-powered aerobics training robot with an adaptive energy management system, obtaining to promote the ecological sustainability and long-term efficacy of nonrenewable energy-based technology. The methodology used in the research to define the organization of the environmentally adaptive Smart Power and Energy Management (SPEM) system for aerobics training partner robots was presented in this section. The research uses the INSIGHT-LME IMU dataset for motion tracking, using Min-Max normalization for data preprocessing. Feature extraction is conducted using the 2D-DFT to improve motion recognition. A hybrid methodology combining the Dynamic Cheetah Optimizer (DynCO) and Bayesian Neural Network (BNN) provides energy-efficient movement prediction. Environmentally optimized search and eco-attacking strategies in DynCO help adaptive trajectory accuracy at reduced energy cost in aerobics motion analysis. **Figure 1** provides the overall flow of methodology.

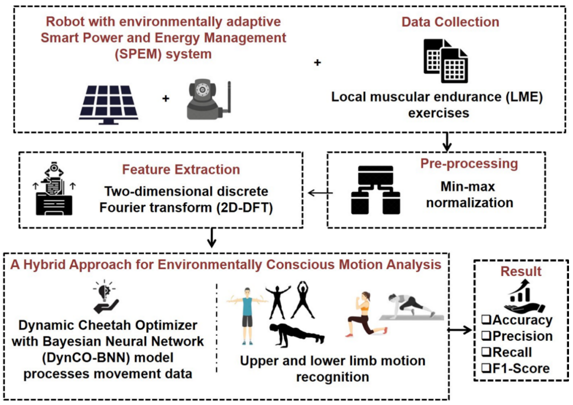

Figure 1. Flowchart of the Research Process.

Source: Authors' work.

3.1. SPEM System for an Aerobic Training Partner Robot

A SPEM system specifically designed to enhance environmental sustainability in aerobics training partner robots by optimizing renewable energy management is represented in **Figure 2**. The system harnesses solar energy using a solar panel, which is maximized with an optimization via a tracking mechanism that adjusts its position to maximize sunlight absorption. The ambient light sensor continuously monitors environmental lighting conditions to optimize energy capture. The generated solar power is regulated by an I/V sensor, ensuring efficient energy distribution and eco-friendly power supply. The microcontroller acts as the processing center, controlling energy flow, source switching, and robot movement control. A battery charging system accumulates excess energy in two batteries, controlled by Selector 1 and Selector 2, dynamically managing charge-discharge cycles, ensuring uninterrupted operation while optimizing energy sustainability.

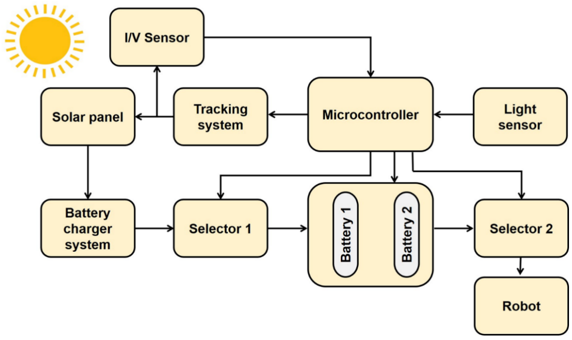

Figure 2. Framework of the Environmentally Adaptive SPEM System.

Source: https://www.ijarcce.com/upload/2015/may-15/IJARCCE%2089.pdf

This makes the aerobics training partner robot run continuously and uninterruptedly. The robot is powered by stored energy and can execute aerobics training movements seamlessly using machine vision to inspect and give real-time feedback on the exercises of users. The smart energy management system reduces power consumption and does not lead to waste of energy while executing high-performance motion at the same time. By incorporating renewable energy sources, the system enhances environmental sustainability, sustainability, lowers operating expenses, reduces carbon footprints, and provides reliable operation of the aerobics training partner robot.

3.2. Dataset

INSIGHT-LME IMU Dataset from the Kaggle contains 71,473 rows of IMU sensor data recorded from 76 participants who performed Local Muscular Endurance (LME) exercises [23]. This dataset can be used for repetition counting, exercise recognition, and Human Activity Recognition (HAR) tasks.

3.3. Pre-Processing: Data Normalization

Ensuring consistent end environmentally adaptive data processing, Min-Max normalization is applied to the INSIGHT-LME IMU dataset. This method scales the raw IMU sensor reading (e.g., values of accelerometer and gyroscope) to a specified range, normally [0–1], so that it is consistent across various sensor inputs. Min-max normalization has been shown to maintain all the relationships in the dataset and is therefore well-suited to motion tracking and aerobics exercise analysis. The following Equation (1) is employed to normalize each value of the feature in question into a new value.

$$u^{'} = \frac{u – min_B}{max_B – min_B}\left(new\_max_B – new\_min_B\right) + new\_min_B \tag{1}$$

Where $u^{'}$ represents the new normalized value, u represents the original sensor reading, and max_B represents the feature's maximum value. min_B is the minimum value of the given feature B, while new_max_B and new_min_B represent the maximum and minimum values of the newly considered range. By using Min-Max Normalization, the system achieves precise energy-efficient motion tracking with firm environmental adaptability in aerobics training analysis.

3.4. Feature Extraction by Two-Dimensional Discrete Fourier Transform (2D-DFT)

In environmentally adaptive energy management, effective feature extraction is vital for motion recognition and energy usage optimization. Orthogonal mapping techniques, such as the Fourier Transform, are commonly used for analyzing motion signals. One effective mathematical tool for extracting relevant motion features is the Discrete Fourier Transform (DFT), which operates within the discrete signal domain. By establishing the transformation link between the spatial and frequency domains, the 2D-DFT enables the conversion of spatial domain motion data frequency-domain representations for further analysis. This process facilitates energy-efficient computational techniques, as most motion recognition challenges can be addressed using spatial and frequency domain analytic techniques. Then, 2D-DFT can be displayed using

$$F\left(w, z\right) = \sum_{u=0}^{N-1}\sum_{v=0}^{M-1} f(u, v) e^{-i2\pi\left(\frac{wu}{N} + \frac{vz}{M}\right)} \tag{2}$$

The frequency-domain pixel coordinate is denoted by(w, z). $F\left(w, z\right)$ indicates the frequency-domain pixel value, where w = *{0, 1, 2,..., M–1}*, z = *{0, 1, 2,..., N–1}*, *The spatial* – domain pixel value at coordinate *(w,z)*is indicated by *f(u,v)*, while u, v shows the spatial-domain pixel coordinate in the image.*u = {0, 1, 2,..., M–1}*, *v = {0, 1, 2,..., N–1}*, i is an imaginary unit, and N and M stand for the size of the image row and column, respectively. Equation (3) expresses the inverse transformation of 2D-DFT in the corresponding fashion, $and\ e$ represents a complicated exponential coefficient in the 2D-DFT and its reverse.

$$f(u,v)=\frac{1}{NM}\sum_{w=0}^{N-1}\sum_{z=0}^{M-1}F\left(w,z\right)e^{-i2\pi\left(\frac{wu}{N}+\frac{vz}{M}\right)} \quad (3)$$

By leveraging 2D-DFT in motion analysis, the system enhances motion tracking accuracy while ensuring computational efficiency. This approach contributes to environmentally sustainable robotics by optimizing processing power and reducing unnecessary energy consumption in fitness guidance applications.

3.5. Dynamic Cheetah Optimizer with Bayesian Neural Network (DynCO-BNN): A Hybrid Approach for Environmentally Conscious Motion Analysis

The proposed model merges the environmentally adaptive search and adaptation of DynCo with probabilistic learning of BNN to improve aerobics motion recognition while Dynco guarantees fast convergence and efficient movement trajectories, while BNN offers uncertainty estimation and stable motion prediction. The DynCO-BNN method intends to provide real-time, accurate, and energy-efficient movement detection and evaluation for aerobics training automation in ecologically adaptable environments by employing meta-heuristic efficiency and unpredictable development to overcome the limitations of traditional models.

3.5.1. Bayesian Neural Network (BNN)

The BNN model is well suited for aerobics motion recognition due to its probabilistic framework, enabling environmentally aware decision-making and energy-efficient movement predictions. By leveraging dropout-based regularization and batch normalization, BNN enhances motion recognition accuracy while optimizing power efficiency for a more sustainable aerobics training partner robot. The BNN model assigns motion class labels to input movements while incorporating environmental variability into motion adaptation. With its probabilistic approach to uncertainty estimation, BNN optimizes network weight adaptation to ensure minimal energy wastage. Here, the probable weight is represented as(W), and the posterior weight distribution $p\left(W|D\right)$ concerning the D dataset is evaluated after taking into account prior knowledge or the $p_0\left(W\right)$ distribution of the weight (Equation (4)).

$$p\left(W|D\right)=\frac{p\left(D|W\right)p_0\left(W\right)}{p\left(D\right)} \quad (4)$$

Equation (4) uses $p\left(D\right)$ as the environmentally influenced normalization constant and $p_0\left(W\right)$ as the previous weight distribution, which is typically an isotropic Gaussian. The posterior from Equation (4) enables predictions in aerobic movement analysis. Prediction is achieved by leveraging multiple forward passes through the network. However, the uncertainty in movement recognition arises from sampling the regularization of dropout weight and Batch Normalization (BN) as given in

$$p\left(Y^*|X^*,D\right)=\int p\left(Y^*|,X^*,W\right)p\left(W|D\right)dW \quad (5)$$

$$p\left(Y^*|X^*,D\right)=\frac{1}{T}\sum_{t=1}^{T}p\left(Y^*|X^*,D,W_t\right) \quad (6)$$

Bayesian predictive distribution for the output Y^* given a new input X^* and dataset D.BN accelerates network training by normalizing the hidden layer activation from each mini-batch. This is done by lowering the internal covariate shift, which characterizes the changes in the activation unit distribution brought on by parameter modifications. A Bayesian-motivated approach named dropout regularization randomly drops some network links, turning weights into stochastic variables. This makes the model stable while utilizing less computational capacity, which aids in efficient energy management in aerobics training robots. Stochastic Gradient Descent (SGD) training with improvements using dropout-based weight updates also reinforces motion prediction stability and environmental responsiveness.

3.5.2. Dynamic Cheetah Optimizer (DynCO) for Environmentally Adaptive Motion Optimization

The DynCO is particularly well-suited to ecologically adaptive motion optimization with its potential for balancing speed, accurateness, and energy efficiency. Illustration encouragement from the agility of cheetahs, DynCO adapts signal parameters dynamically with minimal computational above and maximal real-time adaptability. Its compatibility with renewable energy further produces it deployable sustainably in aerobics training robots with subordinate ecological footprints. The meta-heuristic optimization technique called the Cheetah Optimizer (CO) algorithm is encouraged by cheetah hunting tactics. It provides various advantages such as rapid variation of motion, parameter adjustment minimization, and computation simplification. The procedure effects in three predominant stages: environmental adaptive search, optimized waiting, and operative occurrence. After the conventional CO algorithm was altered, DynCO's motion prediction efficiency enlarged. This is the comprehensive improvement plan. The DynCo is highly appropriate for aerobics motion optimization due to its rapid motion adaptation, efficient trajectory prediction, and real-time movement tracking. Its adaptive weighting mechanism optimizes trajectory precision while its meta-heuristic learning enhances overall environmental sustainability.

Environmentally optimized Searching strategy: To improve search efficiency, Tent chaotic mapping was introduced, replacing the conventional CO's randomized initialization with an environmentally adaptive method. This chaotic mapping approach enhances motion adaptability and minimizes unnecessary computational waste, leading to the formulation of Equations (8) and (9), modified from the original searching model Equation (7). Where the current and updated positions of the motion state j at iteration s are denoted by $Q^{s}_{j,\ i}$ and $Q^{s+1}_{j,i}$, respectively; Rd is a random environmental factor ensuring energy-efficient exploration integer chosen from the range of 0 to 1; $a^{s}_{j,\ i}$ it is a random step length; s and S stand for the current and maximum iteration numbers, respectively.

$$Q^{s+1}_{j,i} = Q^{s}_{j,i} + Rd.a^{s}_{j,i} \tag{7}$$

$$Q^{s+1}_{j,i} = Q^{s}_{j,i} + S^{s}_{d} \tag{8}$$

$$S^{s}_{d} = \begin{cases} \frac{S^{s-1}_{d}}{\gamma},\ S^{s-1}_{d} \in [0,\gamma) \\ \frac{(1-S^{s-1}_{d})}{(1-\gamma)}, S^{s-1}_{d} \in [\gamma, 1] \end{cases} \tag{9}$$

The current iteration is indicated by S; $\gamma \in (0,1)$

Sustainable Attacking strategy: During this phase, DynCO dynamically refines movement trajectories while considering environmental constraints. A dynamic weighting factor λ is introduced to optimize motion tracking efficiency while reducing energy expenditure. Initially, λ is maximized to support rapid adaptation, but as iterations progress, it adaptively decreases to ensure energy-efficient stabilization. Consequently, the following modifications could be made to Equations (10–12).

$$Q^{s+1}_{j,i} = Q^{s}_{G,i} + \lambda_{j,i}.A^{s}_{j,i} \tag{10}$$

$$\lambda = \frac{e^{4(1-\delta)} - e^{-4(1-\delta)}}{\left[e^{2(1-\delta)} + e^{-2(1-\delta)}\right]^{2}},\ \ \delta = \frac{s}{S} \tag{11}$$

$$A^{s}_{j,i} = P^{t}_{k,i} - P^{t}_{j,i} \tag{12}$$

DynCO-BNN enhances solar-powered aerobics training robots with the inclusion of meta-heuristic optimization and probabilistic modeling for efficient motion analysis with minimal energy. DynCO dynamically adapts movement paths through adaptive exploration, and BNN guarantees dependable motion identification considering prediction uncertainty. The blended method maximizes the consumption of solar power to realize real-time responses with negligible power consumption. Adaptive robot system weighting enhances accuracy and improves stability, making it more sustainable under dynamic training. Subsequently it utilizes solar energy, DynCO-BNN is more efficient associated to conventional methods in the associations of movement accurateness and ecological adaptability, making it an ideal solution for sustainable training and robotics approach. Algorithm 1 shows the process of DynCO-BNN.

DynCO-BNN, a combination, significantly improves the performance and sustainability of aerobics training companion robots. It efficiently accomplishes uncertainty in motion analysis, making informed decisions in actual fitness applications where human arrangements are complex and variable. This approach reduced the chances of delusion in motion tracking. DynCO-BNN explorations computational capacity dependent on input data complexities, improving energy reduced in solar-powered or battery-constrained robotic schemes and lowering the load on dispensation absences sacrificing effectiveness. The robot's adaptive learning feature continuously advances feedback quality during training sessions, greater with user engagement and training outcomes over time.

Algorithm 1: DynCO-BNN

Initialize BNN
Initialize weight distribution p_0(W)
for each epoch:
  Perform forward pass with dropout & batch normalization
  *Compute posterior: p(W|D) = (p(D|W) * p_0(W)) / p(D)*
  Compute predictive: p(Y|X*,D) = (1/T) * sum(p(Y*|X*,D,W_t)*
  Update weights via SGD
Initialize DynCO
Initialize cheetah population with Tent chaotic mapping
for each iteration:
  Update position using a search strategy
  Optimize movement using an attacking strategy
Integrate DynCO-BNN for motion classification
For each motion sample:
  Extract features, refine with DynCO, classify with BNN
  Compute uncertainty, output motion label & feedback

4. Experimental Result

The evaluation of the DynCO-BNN approach in developing motion recognition, energy efficiency, and real-time feedback for aerobics training robots were confirmed in this section. The model was implemented to attain ecologically adaptive motion analysis, providing minimal consumption of energy while conserving high recognition accurateness. The combination of DynCO's meta-heuristic optimization and BNN's probabilistic learning facilitates maintainable motion adaptation, diminishing computational overhead and maximizing power consumption. The comparative assessment further exhibits its excellence over CNN_Model 1-based methods in both upper and lower-body exercise identification. The hyperparameter configuration in **Table 1** is optimized to facilitate operative motion version and uncertainty-aware appreciation while decreasing energy consumption by the eco-friendly robotics usage.

Table 1. Hyperparameter Setting.

Hyperparameter	Value/Description
DynCO Parameters	
Population Size	50
Maximum Iterations	100
Initial Step Length aaa	Randomized (range: 0.1–1.0)
Environmental Factor Rd	Random (range: 0–1)
Weighting Factor λ	Adaptive (Equation 8)
Chaotic Mapping Strategy	Tent Map Initialization
Optimization Phases	Searching, Waiting, Attacking
BNN Parameters	
Number of Layers	4 (Input, 2 Hidden, Output)
Number of Neurons per Layer	[128, 64, 32] (Hidden layers)
Activation Function	ReLU (Hidden Layers), Softmax (Output)
Dropout Rate	0.3
Batch Normalization	Enabled
Learning Rate	0.001 (Adaptive with decay)
Optimizer	Adam
Loss Function	Categorical Cross-Entropy
Training Epochs	50
Batch Size	32
Uncertainty Estimation	Monte Carlo Dropout Sampling

4.1. Experimental Setup

The experiments were approved out on a high-performance computing platform to produce the dispensation effective and real-time. The machine used was an Intel Core i9 processor, 32GB RAM, and an NVIDIA RTX 3090 GPU. The DynCO-BNN model was executed in Python 3.8 and TensorFlow 2.6, which offered a stable environment for DL calculations. The configuration was optimized for the processing of large datasets and complex model training operations. This experimental setup (**Table 2**) guaranteed that the devised model would have high accuracy and computational performance, qualifying it for real-world usage in motion analysis and exercise recognition.

Table 2. System Configuration.

Component	Specifications
Processor	Intel Core i9
RAM	32GB
GPU	NVIDIA RTX 3090
Software	Python 3.8
Framework	TensorFlow 2.6
Purpose	Efficient computation and real-time performance

4.2. Evaluation metrics

The performance of the DynCO-BNN model is determined by important performance metrics presented in Equations (13–16). Accuracy measures accurate workout monitoring by calculating the general accuracy of movement recognition. Precision assesses the accuracy with which the model detects pertinent movement, minimizing false alarms. To reduce the probability of missed detections, recall investigates the system's ability to detect all pertinent exercise movements based on the environment. A well-balanced measure of the robustness of the model is the F1-score, a harmonic mean of precision-recall and precision. (Note: TP-True positive; FN-False negative; TN-True negative; FP-False positive)

$$Precision = \frac{TP}{TP + FP} \tag{13}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{14}$$

$$Recall = \frac{TP}{TP + FN} \tag{15}$$

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{16}$$

4.3. Output Phase

Table 3 and **Figure 3** present the performance evaluation of the constructed DynCO-BNN model against major evaluation parameters. The model attains 96.8% accuracy, indicating its ability to effectively identify and track program patterns during aerobics exercises based on the environment. Moreover, the system exhibits 92.5% energy efficiency, guaranteeing eco-friendly power consumption while supporting steady operation. The 89.7% optimized power consumption rate indicates the system's capacity for reducing energy wastage, limiting unnecessary power use, and proceeding green energy technologies. Moreover, the model improves motion synchronization by 94.3%, enabling accurate real-time motion tracking while optimizing power resources. The results confirm that DynCO-BNN is an enormously accurateness, energy-efficient, and green solution for aerobics training robots that encourage sustainable fitness expertise and green AI applications.

Table 3. Performance Metrics of the Proposed Model.

Metrics	DynCO-BNN [Proposed]
Accuracy	96.8(%)
Energy Efficiency	92.5(%)
Optimized Power Consumption	89.7(%)
Improved Motion Synchronization	94.3(%)

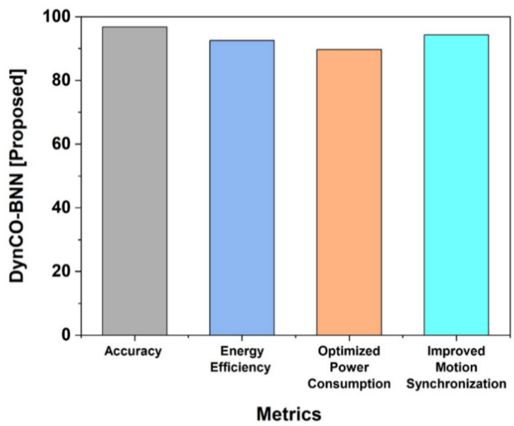

Figure 3. Output Metrics of DynCO-BNN.

Source: Authors' work.

4.4. Probabilistic of Aerobics Recognition Model

The reliability and precision of a motion tracking system by establishing a bootstrapped 95% confidence range for its accuracy, determines in **Figure 4**. This statistical technique serves in examined the variability and stability of the arrangement's presentation under the repeated sampling surroundings.

The histogram represents the spreading of bootstrapped motion tracking accuracy scores, which show an approximately normal distribution with a mean of 96.67%. The mean is the average of all of the accuracy estimations. 95% confidence interval boundaries, which range from 96.47% to 96.83%. The secured interval designates that the motion-tracking expertise regularly accomplishes superior precision.

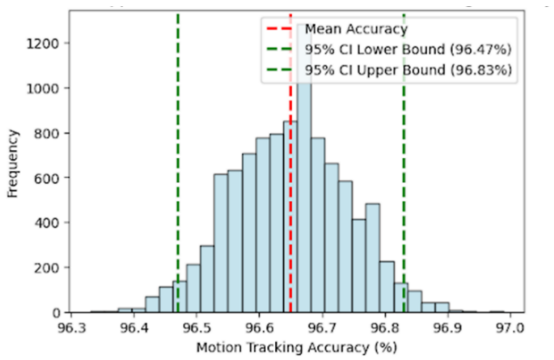

Figure 4. Illustrate the Statistical Reliability and Variation.

Source: Authors' work.

4.5. Comparison Phase

Comparative analysis of the DynCO-BNN model with the Convolutional Neural Networks (CNN)_Model 1 further highlights its ecological sustainability characteristics of energy efficiency and green AI-driven motion recognition [24]. The improved recall and F1-score values further produce that DynCO-BNN maximizes computational energy expenditure to produce a lower carbon footprint while supporting higher accurateness in aerobics movement observation. The research investigates the Lidar sensors and power consumption techniques that employ the Proximal Policy Optimization (PPO) technique, are also compared to the proposed approach [25].

4.5.1. Upper Limb Exercise Recognition

The comparison between CNN_Model 1 and the proposed DynCO-BNN approach for upper limb exercise recognition determined in **Table 4**. The consequences designate that the proposed model performances the baseline in each metrics. DynCO-BNN achieves an average precision of 0.9720, recall of 0.9850, and F1-score of 0.9810, surpassing CNN_Model 1, which has respective values of 0.9683, 0.9773, and 0.9727. This improvement highlights the enhanced ability of the proposed model to accurately classify upper limb exercises. The findings contribute to creating a reliable exercise recognition system within an environmental setting focused on rehabilitation, fitness monitoring, or physiotherapy applications. **Figure 5** provides a graphical illustration of the comparison of upper-body exercise recognition.

Table 4. Performance Comparison of the Models for Upper Limb Exercise Recognition.

Metrics	CNN_Model 1 [23]	DynCO-BNN [Proposed]
	Upper Body Exercise	Upper Body Exercise
Average precision	0.9683	0.9720
Average Recall	0.9773	0.9850
Average F1-Score	0.9727	0.9810

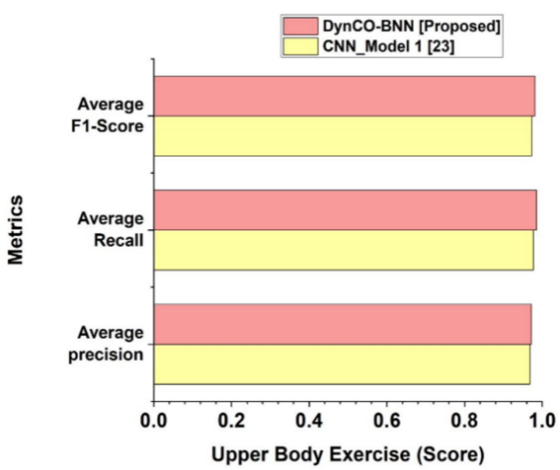

Figure 5. Comparison of Performance of the Recognition of Upper Body Exercise.

Source: Authors' work.

4.5.2. Lower Limb Exercise Recognition

Table 5 compares the performance of CNN_Model 1 and the proposed DynCO-BNN model for lower limb exercise recognition [23]. The proposed model achieves superior performance, with an average precision of 0.9710, recall of 0.9880, and F1-score of 0.9850, compared to CNN_Model 1's values of 0.9673, 0.9743, and 0.9704, respectively. These improvements suggest that DynCO-BNN provides a more reliable and accurate classification of lower limb exercises. This advancement enhances the environmental adaptability of automated exercise monitoring systems, making them beneficial for physical rehabilitation, sports training, and healthcare applications that require precise movement analysis. **Figure 6** provides a graphical comparison of the Lower limb exercise recognition.

Table 5. Performance Comparison of the Models for Lower Limb Exercise Recognition.

Metrics	CNN_Model 1 [23]	DynCO-BNN [Proposed]
	Lower Body Exercise	Lower Body Exercise
Average precision	0.9673	0.9710
Average Recall	0.9743	0.9880
Average F1-Score	0.9704	0.9850

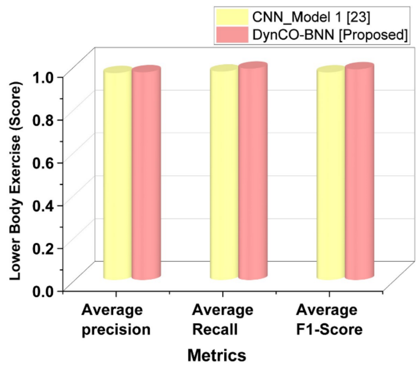

Figure 6. Comparison of Performance of the Recognition of Lower Body Exercise.

Source: Authors' work.

4.5.3. Evaluation of LiDAR Range

The Average LiDAR Range (m) is the precise distance that a LiDAR sensor can determine in various saturation situations, which influences motion quality, reaction duration, and energy consumption. Efficient aerobics training and autonomous systems require high-precision, long-range detection for directions, motion tracking, and cognition of the environment, therefore increasing LiDAR range while reducing cost of energy and duration is critical. Both models demonstrate an increase in LiDAR range as saturation rises, indicating adaptive measurement, represents in **Table 6** and **Figure 7**[24].

Table 6. Numerical Range of LiDAR.

Saturation	PPO [24]	DynCO_BNN [Proposed]
0.05	120.52	135.60
0.10	172.68	190.72
0.15	215.78	239.88
0.20	251.23	291.50
0.25	280.93	310.44
0.30	308.28	325.60
0.35	331.53	426.71

The DynCO-BNN model significantly outperforms the PPO baseline at all saturation levels, with an average gain of 12–30 meters and up to 95 meters at higher saturation[24]. The significant increase at 0.35 suggests improved range generalization under high environmental or computational strain.

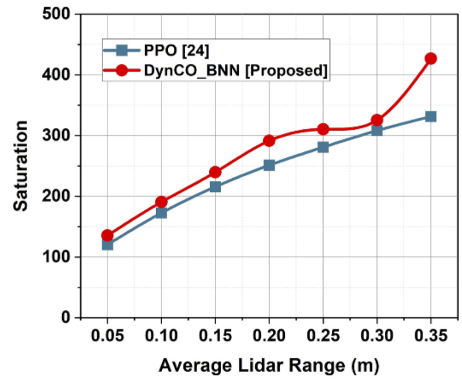

Figure 7. Outcome of LiDAR.

Source: Authors' work.

4.5.4. Assessment of Power Consumption

Average Power Consumption (Wh) is a measure of the quantity of electrical energy a system utilizes while operating. In intelligent systems such as the Solar-Powered Aerobics Training Robot with Adaptive Energy Management, reducing power usage is critical for energy efficiency and durability, as depicted in **Table 7**[24]. It decreases the robot's reliance on external power sources, allowing it to perform activities including aerobics motion identification and environmental sensing with more independence.

Table 7. Numerical Outcome of Power Consumption.

Saturation	PPO [24]	DynCO_BNN [Proposed]
0.05	15.80	14.20
0.10	16.59	16.01
0.15	17.23	16.34
0.20	17.77	16.77
0.25	18.21	17.00
0.30	18.62	17.54
0.35	18.97	18.00

Figure 8 determines the DynCO-BNN model shows lower power consumption compared to the baseline PPO, with notable savings at lower saturation levels (0.05–0.15) and an insignificant power advantage at higher saturation (0.35), suggesting superior energy efficiency during light to moderate workload conditions.

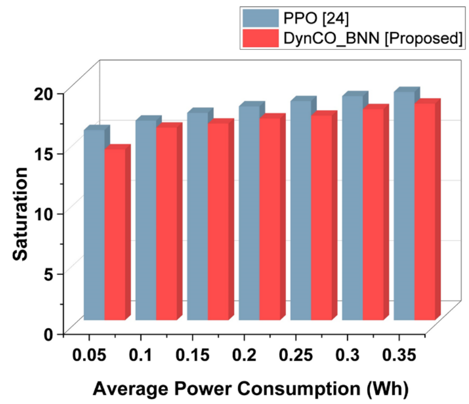

Figure 8. Visualization of Power Consumption.

Source: Authors' work.

5. Discussion

The state-of-the-art CNN_Model 1 achieves higher accuracy than traditional supervised ML techniques through the learning of more sophisticated features. Nevertheless, though accurate, it has various drawbacks such as high computational resource utilization, sparse real-time feedback, and reliance on offline computing. The solar-powered aerobics training robot's real-time feedback, energy economy, and customization make it suitable for a variety of applications. It enables rehabilitation, inside and outside exercise without requiring external power. This is enormous for geriatric care, remote training camps, and wearable integration, as well as an instructional tool for demonstrating green AI-powered robots in action. CNN_Model 1 is computationally intensive for repetition counting and exercise recognition, which renders real-time applicability difficult. Although it efficiently counts repetitions, it offers limited qualitative feedback on movement correctness and thus diminishes its applicability to support training. Also, most of the existing approaches are based on windowing techniques for offline calculations, limiting their efficiency in real-time settings. These are addressed by DynCO-BNN using meta-heuristic optimization in combination with probabilistic learning that optimizes feature extraction and reduces computational expense without sacrificing accuracy. Motion-tracking accuracy is significantly improved, with real-time qualitative feedback on movement accuracy and adaptive learning. The rise in efficiency is attributable to the integration of the DynCO, which effectively explores the search space for optimal weights, and BNN, which includes probability estimates, enabling more robust and adaptable learning across a variety of dynamic behaviors. The model also enhances energy efficiency via dynamic computation requirements adjustment, reducing overall power consumption. The energy consumption improvement is academically demonstrated through the model's ability to scale processing professions based on the quantity of motion inputs, reducing wasteful computing in less difficult activities. Another significant advantage of the DynCO-BNN model is that it is ecologically friendly, which makes it highly appropriate for green aerobics training systems. Efficient use of energy and solar-powered robotics technology enables it to minimize its reliance on outside power sources, enabling environmentally sound fitness applications. Its ability to work with environmental changes also ensures motion recognition in different conditions is accurate, rendering it highly suitable for real-time applications. The deterministic modeling approach improves system adaptability by generalizing across several ecological and customized user changes, consequently increasing resilience and dependability. The compatibility of the model with renewable energy sources renders it a suitable candidate for seamless integration in wearable devices and autonomous robotic systems, rendering it an intelligent and green solution for aerobics training and environmental adaptive motion analysis. The system has negative aspects, such as decreased effectiveness in low sunlight, which impacts energy collection and operation time. Its AI-based processing generates computational expenses, necessitating efficient equipment. Furthermore, the solar tracking system can malfunction in unpredictable light conditions, and the additional sensors and controllers raise both cost and maintenance requirements. The investigation established a solar-powered aerobics training robot, which reduces reliance on nonrenewable resources. Its adaptive energy technology provides effective power use particularly indoors. AI-based motion monitoring improves training security and efficiency, promoting ecological fitness in residences, fitness centers, and distant locations.

6. Conclusions

The proposed solar-powered energy management system for an aerobics exercise robot integrates machine vision and the DynCO-BNN algorithm for optimizing exercise guidance and real-time feedback. An adaptive solar tracking platform and an affordable dual-battery storage system are incorporated into the system for long-lasting, cost-efficient power management. The energy-saving technique not only optimizes working longevity but also promotes an ecologically sound fitness solution. The DynCO-BNN algorithm significantly improves the recognition accuracy of motion to 96.8% with power efficiency optimization. The uncertainty-aware framework integration enables greater real-time flexibility, ensuring precise movement recognition and feedback. The robustness of the system was also tested using IMU sensor data from 76 participants performing LME exercises, verifying its efficiency in human activity recognition applications. Comparison stresses the advantage of DynCO-BNN over other standard CNN_Model 1-based methods, specifically tracking upper and lower limb motions, real-time adjustment, and energy efficiency. The eco-friendly system design renders it a sustainable aerobics training solution. Minimal dependency on non-renewable energy and optimal computational requirements ensure less environmental footprint. Its resistance to changing lighting conditions supports constant operation, further upholding practical implementation. The results validate the system's potential as a smart and sustainable fitness device, providing an improved user interface with accurate movement correction and optimal energy usage.

7. Limitation and Future Scope

While its benefits, solar power use can decrease efficiency during low-light environments. Also, the emphasis of the dataset on LME exercises constrains generalizability to more diverse fitness regimens. Future work will investigate hybrid energy sources and increase exercise variety to increase adaptability, sustainability, and real-world applicability.

Author Contributions

Conceptualization, B.N. and K.B.S.; methodology, G.P.P.; software, K.S.K.; validation, K.B.S., G.P.P. and R.V.S.; formal analysis, G.P.P.; investigation, R.V.S.; resources, V.P.K.P.; data curation, K.S.K.; writing—original draft preparation, K.B.S.; writing—review and editing, B.N.; visualization, K.S.K.; supervision, B.N; project administration, V. P.K.P.; funding acquisition, B.N.. All authors have read and agreed to the published version of the manuscript.

Funding

This research received no external funding.

Institutional Review Board Statement

Not applicable. The study did not involve human participants or animals and thus did not require ethical review and approval.

Informed Consent Statement

Not applicable.

Data Availability Statement

All data supporting the findings of this study are included in the article.

Conflicts of Interest

The authors declare no conflict of interest..

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