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Research paper

A Deep Learning Framework for Human Motion Recognition Using Compact CNNs and Swarm Optimization

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Abstract

Aerobic exercise is essential to maintain the cardiovascular system's health, yet accurate analysis of its complex motions poses severe challenges. Traditional methods often encounter computational loads, overfitting, and unfavorable generalization in real applications. In trying to resolve these issues, this work introduces the MCT-MCT-MCT-MCT-MCT-MCT-MCT-HCNanoNet-AM framework, which combines motion capture technology (MCT) and a Humboldt Squid Optimization Algorithm (HSOA)-optimized Compact-NanoNet Deep Convolutional Neural Network (CNanoNet). This blended approach is going to enhance the accuracy and efficiency of aerobic movement analysis. The MCT-MCT-MCT-MCT-MCT-MCT-MCT-HCNanoNet-AM system workflow incorporates several key steps. Initially, high-speed motion capture technology is utilized to capture data. The raw data are processed beforehand using Mean Curvature Flow, which is a technique to remove noise at the first step. Afterwards, feature extraction and movement detection are done using the CNanoNet model. The HSOA is then employed to optimize the CNanoNet for improving model performance. The optimized model is then utilized for real-time aerobic movement recognition with personalized feedback to the users. Experimental results indicate that the MCT-HCNanoNet-AM system noticeably enhances the recognition and classification of aerobic movements with an exceptional set of 99.98% accuracy, 99.99% precision, 99.986% specificity, 99.99% recall, and 99.98% F-Score. The system takes 91 seconds in computation and area under the curve (AUC) of 0.9976. Integration of real-time feedback mechanisms not only helps in refining the techniques of users but also in the prevention of injuries by identifying potential risks. Overall, the MCT-HCNanoNet-AM system is a major advance in aerobic movement recognition technology that enhances performance as well as overall physical well-being through innovative technological advancements.

Keywords: *Motion Capture Technology; Compact-Nanonet Deep Convolutional Neural Network (Cnanonet); Humboldt Squid Optimization Algorithm (HSOA); Aerobic Movement Analysis; Mean Curvature Flow.*

1. Introduction

Aerobic movements are dynamic exercises that significantly improve cardiovascular fitness through rhythmic and continuous activity [1]. These exercises engage multiple muscle groups, leading to enhanced endurance, flexibility, and overall physical well-being [2], [3]. Traditionally, aerobics incorporates choreographed routines often synchronized with music, making it a widely practiced form of exercise for several decades [4], [5]. Typical aerobic activities, such as jumping, running, stretching, and dancing, are designed to elevate oxygen circulation by promoting heart health and stamina [6]. In recent years, the integration of motion capture technology into aerobic exercise monitoring has gained popularity. This innovative technology utilizes sensors and cameras to accurately record body movements, providing detailed data regarding joint angles, limb positions, and movement trajectories [7]. Such precision allows for a thorough evaluation of exercise performance, facilitating improvements in technique and overall effectiveness [8]. The collaborative application of motion capture technology with machine learning algorithms represents a significant advancement in the analysis of aerobic movements [9,10]. These algorithms possess the capability to identify subtle variations in movement patterns, enabling automated assessments and quicker feedback mechanisms [11]. This results in enhanced performance analysis accuracy and efficiency, benefiting both casual fitness practitioners and professional athletes [12]. Despite the advantages of current systems employing motion capture and machine learning for aerobic analysis, several challenges persist [13].

The key contributions of the proposed MCT-HCNanoNet-AM method are given below,

- The innovative integration of motion capture technology, Compact-NanoNet Deep Convolutional Neural Network (CNanoNet), and Humboldt Squid Optimization Algorithm (HSOA) offers a unique solution for analyzing aerobic movements.
- The Compact-NanoNet is designed to be computationally efficient, making it suitable for real-time motion capture data analysis, even in resource-constrained environments.
- The HSOA enhances the Compact-NanoNet's performance by optimizing parameters, which enhances accuracy and adaptability to dynamic movement patterns.
- The proposed MCT-HCNanoNet-AM method enables real-time feedback on aerobic activities, delivering immediate insights into performance and recommending necessary corrections.
- The combination of Compact-NanoNet and HSOA allows for scalable analysis, handling large volumes of motion capture data while maintaining high efficiency shown in Figure 1(a).
- By identifying potential risks and deviations from correct form, the system helps prevent injuries and improve overall safety.
- The accurate analysis of aerobic movements provides valuable insights for optimizing performance, enhancing endurance, and achieving fitness goals.
- The system offers an objective assessment of aerobic movements, reducing subjectivity and improving the reliability of performance evaluation.

The remainder of this paper is organized as follows: Section 2 provides a comprehensive review of existing approaches and challenges in analyzing aerobic movements using motion capture technology and machine learning algorithms. Section 3 presents the proposed MCT-HCNanoNet-AM framework. Section 4 outlines the experimental setup, evaluation metrics, and performance comparison with current techniques. Finally, Section 5 concludes with key findings and suggests potential avenues for future research.

2. Related works

This section reviews previous research on the application of motion capture technology and machine learning in the analysis of aerobic movements. Some recent studies are highlighted below. In 2022, Liu, Q., presented a model that integrated a deep neural network and Long Short-Term Memory (LSTM) networks with a motion capture technology for aerobic movement analysis (MCT-DNN-LSTM-AM). This model established the relative motion relationship between camera positions across continuous video sequences [14]. Additionally, transfer learning techniques facilitated the adaptation of pre-trained network parameters for the classification task related to video sequence movement recognition [15]. The LSTM structure effectively captured and retained long-term image memory information, accounting for the temporal correlations inherent in video sequences. However, the model exhibited low accuracy despite achieving a high recall value [16]. In 2024, Yihan, M., suggested the design and optimization of an aerobics movement recognition system that utilized high-dimensional biotechnological data. Biosensing technology and wearable devices collected real-time, multidimensional physiological signal data from critical anatomical regions of athletes [17]. The system was constructed using convolutional neural networks (CNNs), and Long Short-Term Memory (LSTM) networks were employed to attain accurate classification and recognition of movement actions (BT-CNN-LSTM-AM). Optimization of model performance was achieved through parameter selection and strategies, including Xavier initialization, the cross-entropy loss function, and the Adam optimizer [18], [19]. It has high accuracy with high computation time. In 2021, Wang, Q., and Wang, M., presented an automatic aerobics movement recognition method that utilized three-dimensional convolutional networks along with multilabel classification. To mitigate the loss of temporal information associated with two-dimensional convolutional neural networks (CNNs) during feature extraction, the research employed three-dimensional convolutional networks for aerobics movement analysis (MCT-2DCNN-AM). This methodology effectively captured features in both time and space, facilitating multiple binary classifications to achieve multilabel classification [20,21]. However, it has high Specificity with low accuracy. In 2023, Zuo, N., and Liu, J.A. constructed a multi-layer pyramid structure to segment aerobics video images for detecting key frames and the frame with the highest energy value to generate a binary image. A standardized aerobic movement recognition model was developed by employing a convolutional neural network to identify multi-objective feature vectors within the image [22]. A machine learning framework was then established using a binary classifier to achieve aerobics movement recognition, based on vector constraints of impact strength, as well as spatial and frequency domain vectors. It has low recall value and high computation time [23], [24].

2.1. Problem statement and motivation

The analysis of aerobic movements, which are essential for cardiovascular fitness and physical well-being, is hindered by the limitations of existing systems. These systems often encounter computational efficiency, overfitting, and generalization to real-world environments. [25], [26]. These challenges hinder the development of effective systems for personalized training, injury prevention, and performance optimization. To address these limitations, there is a strong need for a more efficient and accurate approach to aerobic movement analysis. The proposed MCT-HCNanoNet-AM framework, which combines motion capture technology with a Compact-NanoNet Deep Convolutional Neural Network optimized by the Humboldt Squid Optimization Algorithm, offers a promising solution. By leveraging the strengths of these components, MCT-HCNanoNet-AM aims to overcome the challenges of existing methods and provide a more robust and effective tool for analyzing aerobic movements [27], [28].

3. Proposed methodology

In this, the suggested MCT-HCNanoNet-AM framework is presented that bridges motion capture technology with a lightweight deep learning architecture—Compact-NanoNet—tuned with the Humboldt Squid Optimization Algorithm (HSOA) [29], [30]. This methodology aims to facilitate real-time, precise, and scalable aerobic movement recognition to provide extensive analysis for performance enhancement, injury prevention, and biomechanics. The system architecture is depicted in Figure 1(b).

3.1. Acquisition of motion data through optical capture systems

The initial phase of the proposed approach is high-precision data acquisition via an optical motion capture system. The system includes several synchronized infrared cameras and passive reflective markers, which are attached to anatomical landmarks such as the pelvis, thighs, calves, and feet [31], [32]. The Opti Track motion capture system is used since it can provide sub-millimeter accuracy and has already been applied in biomechanical research. The infrared radiation from the cameras is reflected by the markers so that the system can capture the three-dimensional paths of each body segment involved in aerobic exercise [33], [34]. For high-fidelity three-dimensional reconstruction, the system applies geometric calibration to all the cameras and minimizes optical distortion while enhancing data consistency captured. For each marker point, multiple images are taken simultaneously to create a complete spatial reconstruction of movements such as squats, lunges, vertical jumps, and dance sequences. The positions of markers adhere to the Helen Hayes marker set to ensure biomechanical consistency for a wide range of activities [35], [36]. This configuration allows for the capture of joint angles, range of motion, and temporal characteristics crucial in both athletic performance assessment and clinical assessment [37], [38].

3.2. Motion data preprocessing

Raw motion capture data is noisy, carries artifacts, and exhibits discontinuities due to occlusions or huge motion. To eliminate them, the acquired data is preprocessed with Mean Curvature Flow (MCF), which is a mathematical technique based on differential geometry [39], [40]. MCF performs isotropic smoothing and thereby removes spurious oscillations but maintains the required biomechanical qualities such as joint angular velocities, accelerations, and continuity of motion [41,42]. This preprocessing step significantly enhances data reliability and gives a better correct basis for further feature extraction and movement classification. Unlike common filtering methods, MCF can maintain the intrinsic characteristics of complex aerobic movement and is therefore particularly suitable for high-dimensional temporal data obtained in dynamic physical activity [43], [44].

3.3. Feature learning and movement recognition

Once data denoising is performed, the system proceeds to movement feature extraction and aerobic action classification using the Compact-NanoNet Deep Convolutional Neural Network (CNanoNet). CNanoNet is a computationally efficient model suitable for real-time applications as well as in low processing capability scenarios [45].

3.3.1. Feature extraction module

The CNanoNet feature extraction unit is made up of a series of depth-wise separable convolutional layers, combined with batch normalization and ReLU activation. They are structured in Dense Convolutional Blocks, which divide traditional convolution into spatial and channel operations to significantly reduce model complexity and memory footprint. This architecture allows CNanoNet to learn the fine-grained movement features from preprocessed data like joint trajectories, angular displacements, and synchronized limb motions with high precision. The network possesses great representational ability for its minimalist design, which makes it capable of distinguishing between extremely minute variations in movement style.

3.3.2. Movement classification module

Extracted features are passed along a pipeline of classification using global average pooling, dropout regularization, fully connected layers, and a final SoftMax activation for multiclass classification. The movement categories include a variety of aerobic activities such as jumping, dancing, stretching, and squatting. For further improvement in model performance, the Humboldt Squid Optimization Algorithm (HSOA) is used to fine-tune CNanoNet's hyperparameters, for example, learning rate, number of convolutional filters, and dropout values. HSOA applies bio-inspired optimization ideas to efficiently search through the parameter space to enhance generalization and minimize overfitting.

3.4 System capabilities and impact

Combining motion capture data, stable preprocessing, light-weight deep learning, and evolutionary optimization leads to a system that can provide real-time performance feedback. The MCT-HCNanoNet-AM framework proposed provides some key advantages:

- Real-time motion analysis with high-resolution capabilities via sub-millimeter accurate capture systems.
- Noise-resistant preprocessing of data without loss of biomechanical integrity.
- Light-weight deep learning via the compact, yet high-performance CNanoNet architecture.
- Optimization with HSOA for enhanced classification accuracy and generalization of the model.
- Real-time accuracy and scalability for single-fitness measurement and big-data biomechanical studies.

In summary, the MCT-HCNanoNet-AM model ushers in a new era of fast, accurate, and scalable aerobic movement analysis, enabling next-generation fitness monitoring, sports analytics, and rehabilitation.

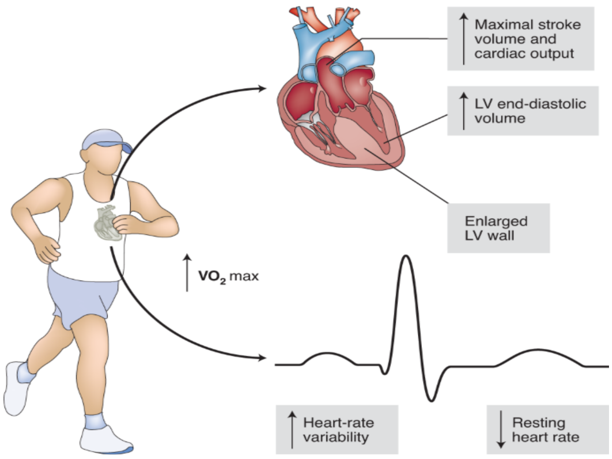

Fig. 1: A) Exercise and Cardiac Health (Compact-NanoNet and HSOA) Motion Capture Technology.

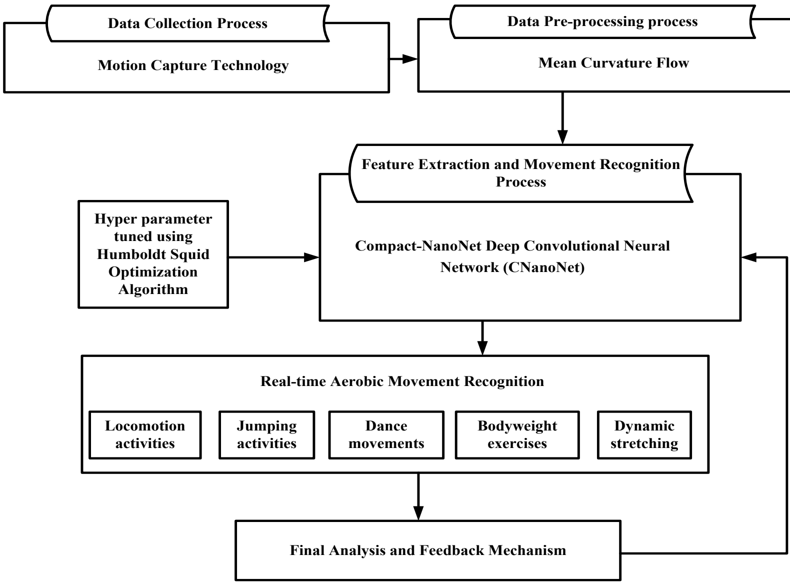

Fig. 1: A) Block Diagram of Proposed MCT-HCNanoNet-AM Method.

3.4. Humboldt squid optimization algorithm (HSOA) for hyperparameter optimization of CNanoNet

For improving the Compact-NanoNet model's performance, the suggested framework utilizes the Humboldt Squid Optimization Algorithm (HSOA). This bio-inspired optimization algorithm captures the intricate behaviors of Humboldt squids like high-speed movement, tactical hunting, and synchronized courting rituals to navigate through and utilize the hyperparameter space effectively. HSOA possesses some key advantages over traditional optimization techniques. It attains a good balance between exploitation and exploration to make the search capable of breaking out of local optima and enhance the likelihood of finding globally optimal solutions. HSOA's dynamic control of its control parameters accelerates convergence, thereby reducing overall training time. Its multi-phase optimization strategy—simulating squid hunting, evasive behavior, inter-squid predation, and mating—comprises strategic diversity to enhance solution quality. In the analogical metaphor, the sea is the search space and the best CNanoNet hyperparameters as the prey. The parameter set is time and again optimized using biologically inspired methods to optimally optimize model performance. With the incorporation of multiple behavioral analogies, HSOA improves convergence rate and solution precision for making the most effective in real-time as well as resource-constrained situations.

3.5. Final integration and feedback mechanism

A last integration and usage would be in the system, where the Compact-NanoNet model is implemented in an actual real-time feedback loop to assess aerobic movement. Upon implementation, it takes in real-time motion capture data and pulls out significant biomechanical features to be classified according to trained patterns for aerobic movements.

The system offers real-time performance feedback in the form of quantitative (e.g., classification accuracy, motion precision, execution time) and qualitative (e.g., form adjustment and technique suggestions) judgments. Visualization tools such as real-time plots and past performance curves allow the user to monitor progress, recognize patterns, and identify precise areas of improvement. With the ability to offer insights based on personal fitness goals and performance levels, the system allows for tailored training and reduces the risk of injury. Mistakes in proper form are automatically detected, and correction feedback is given instantaneously. Furthermore, the objectivity of the system minimizes human bias, providing consistent, reproducible ratings. This real-time decision-support system effectively bridges the gap between technical motion analysis and physical fitness practice, therefore being useful for enhanced performance, safety, and long-term physical well-being.

4. Results and discussion

This section presents the experimental validation of the MCT-HCNanoNet-AM framework, developed for accurate and effective aerobic movement analysis. The proposed system was developed using Python with key libraries like TensorFlow, Keras, NumPy, Pandas, Matplotlib, and OpenCV.

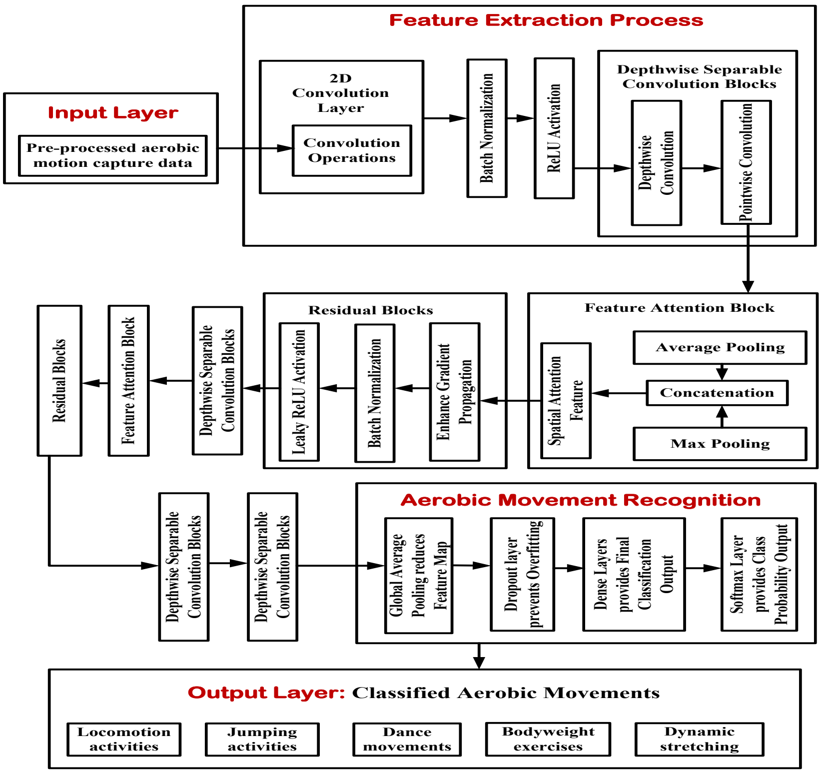

Fig. 2: Architecture Diagram of CNanoNet Model.

Testing was conducted on a machine with an Intel Core i7 processor, 16 GB RAM, and Windows 10 OS. A high-performance computing environment with GPU acceleration and OptiTrack motion capture software was also utilized to deliver real-time processing and precision. The gathered dataset was split into 70% for training, 15% for validation, and 15% for testing, guaranteeing strong model generalization. To assess system performance on a comprehensive level, several metrics were calculated: accuracy, precision, recall, F1-score, specificity, and calculation time. Experimental results show that the suggested MCT-HCNanoNet-AM framework outperformed current benchmark techniques consistently, including: MCT-DNN-LSTM-AM, BT-CNN-LSTM-AM, and MCT-2DCNN-AM. This performance gain is attributed to the efficient CNanoNet architecture and hyperparameter tuning using HSOA. The resulting optimized architecture not only attained higher classification accuracy but also inference speed, thus rendering it workable for real-time applications. Figures 3 to 9 provide detailed comparative analysis across a few categories: Accuracy (Figure 3): MCT-HCNanoNet-AM outperformed traditional models in all types of activity. All values ranged from 1.55% to 44.79%, and the highest improvement was achieved for Locomotion Activities. Precision (Figure 4): Comprehensive improvements in precision (by up to 40.31%) were observed across all types of activity, indicating reduced false positives and more accurate classification. Specificity (Figure 5): The proposed model achieved up to 40.81% higher specificity, identifying non-aerobic movements accurately and minimizing misclassification. Recall (Figure 6): Recall rates improved by as much as 42.63%, reflecting enhanced detection of actual aerobic movement. F1-Score (Figure 7): Proportional improvement in recall and precision led to F1-Score improvements of as much as 39.74%, validating the model's robustness. Computation Time (Figure 8): MCT-HCNanoNet-AM had a notable time reduction for processing, where computation time was as much as 96.907% lower compared to other models. AUC (Figure 9): AUC of the model was enhanced up to 36.65%, which suggests enhanced classification performance.

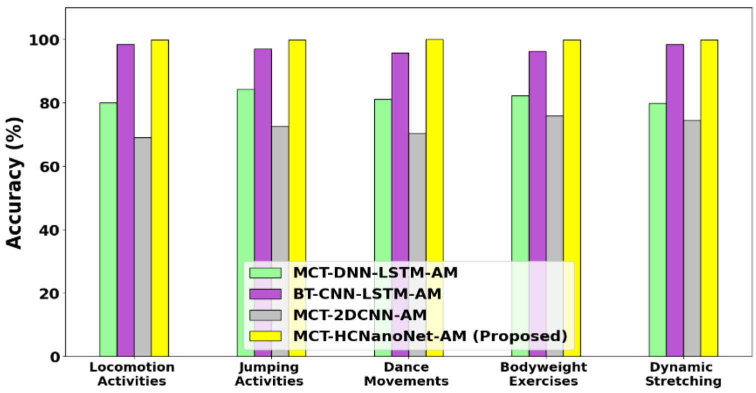

Fig. 3: Accuracy Analysis for Aerobic Movement.

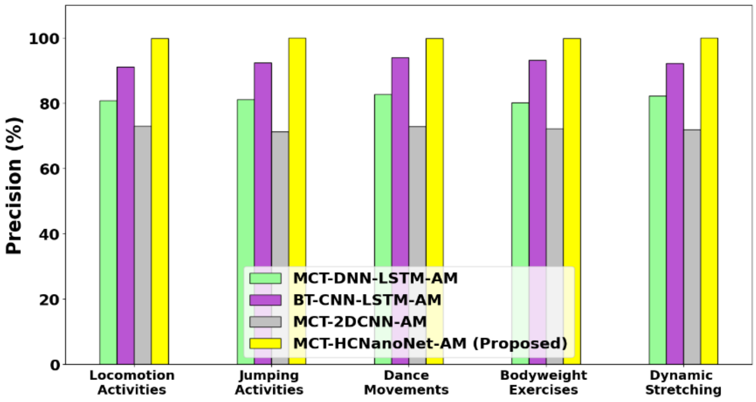

Fig. 4: Precision Analysis for Aerobic Movement.

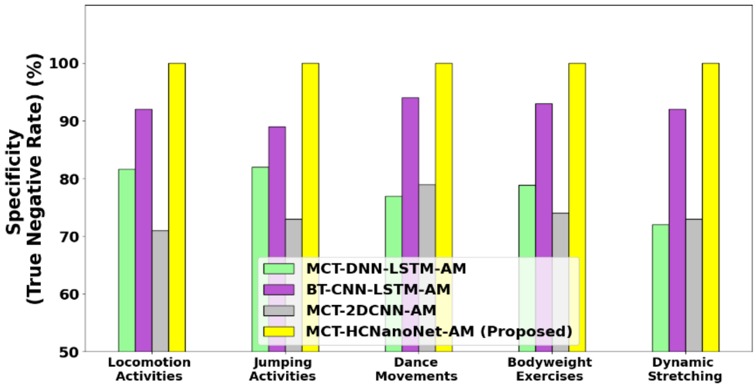

Fig. 5: Specificity Analysis for Aerobic Movement.

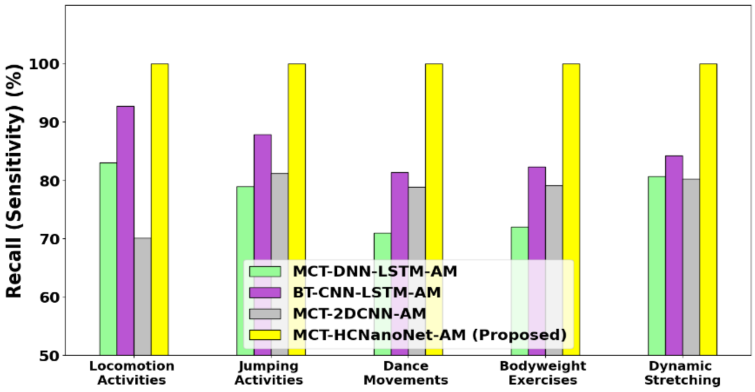

Fig. 6: Recall Analysis for Aerobic Movement.

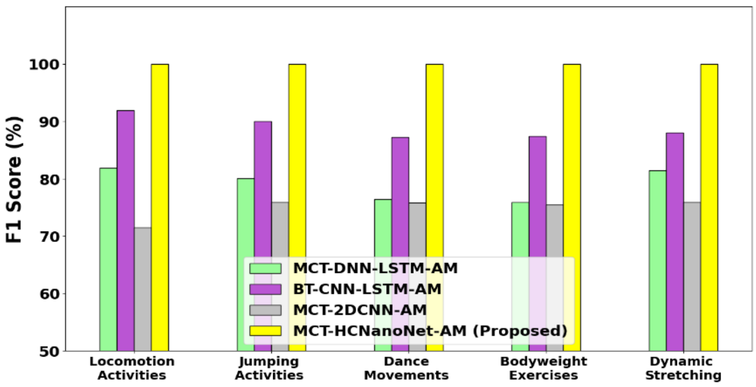

Fig. 7: F1 Score Analysis for Aerobic Movement.

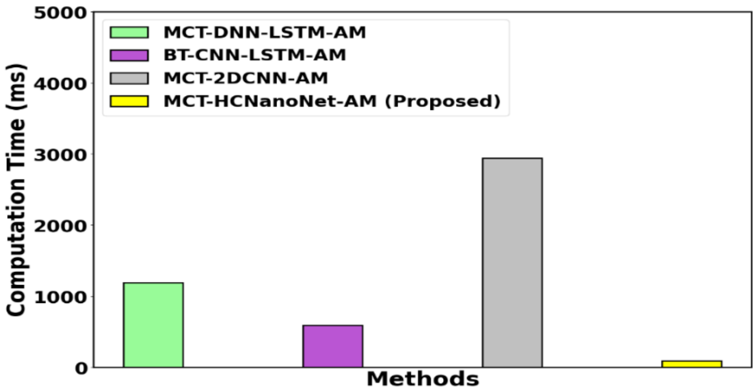

Fig. 8: Computation Time Analysis for Aerobic Movement.

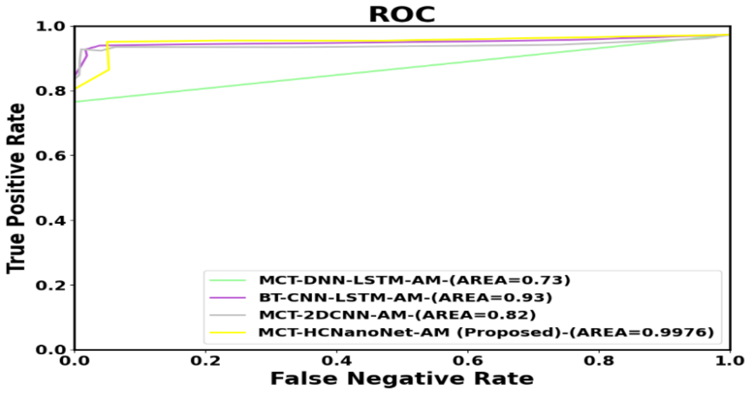

Fig. 9: RoC Analysis for Aerobic Movement.

4.3. Discussion

Integration of motion capture technology, CNanoNet deep convolutional neural network, and Humboldt Squid Optimization Algorithm within the MCT-HCNanoNet-AM framework has produced a robust system for aerobic movement analysis. Quantitatively, the framework delivered significant gains compared to baseline methods:

- Accuracy gains: 22.61%, 2.87%, and 38.07%
- Precision gains: 22.77%, 7.96%, and 38.29%
- Improvement in specificity: 27.98%, 8.71%, and 35.28%
- Improvement in recall: 30.13%, 16.94%, and 28.66%
- Improvement in F1-Score: 26.45%, 12.45%, and 33.48%
- Reduction in computation time: 92.34%, 84.68%, and 96.907%
- Improvement in AUC: 36.65%, 7.26%, and 21.65%

All the performance metrics validate the efficiency and effectiveness of the proposed framework for aerobics and movement classes like locomotion, jumping, dancing, bodyweight exercises, and dynamic stretching.

5. Conclusion

The MCT-HCNanoNet-AM approach offers an end-to-end solution for classifying aerobic movements by integrating motion capture technology, deep learning, and nature-inspired optimization. The application of Mean Curvature Flow preprocessing ensures high-quality data, and the CNanoNet model classifies movements with excellent accuracy. Optimization with HSOA still optimizes the model with better accuracy and reduced computational overhead. The model outperformed traditional models in all the criteria of evaluation. Moreover, its capability for real-time feedback allows users to enhance performance while reducing the risk of injury. The model's success reinforces its use as a tool in fitness and rehabilitation environments. Future enhancements will include multi-modal data integration and API creation to interface with other well-known fitness devices and software for increased adoption of the MCT-HCNanoNet-AM framework as a cornerstone in intelligent motion analysis systems.

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