Heuristic Based Optimized Classifier For HAR

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***Abstract*— Human Activity Recognition plays a pivotal role in various domains, from healthcare to wearable technology. This Paper presents a novel approach that combines heuristic-based feature selection with Particle Swarm Optimization to optimize the performance of HAR classifiers. We begin by employing heuristics to intelligently select relevant features from raw sensor data, reducing dimensionality and enhancing classification efficiency. Subsequently, PSO is applied to fine-tune classifier hyperparameters, achieving superior model accuracy and robustness. Our approach initiates by harnessing heuristics to autonomously discern and select pertinent features from raw sensor data. This intelligent feature selection not only trims the data dimensionality but also elevates the overall efficiency of the classification process. Subsequently, we apply PSO, a nature-inspired optimization algorithm, to meticulously fine-tune classifier hyperparameters.**

Keywords—HAR, Hyperparameter, PSO, Heuristic

I. INTRODUCTION (*HEADING 1*)

The field of Human Activity Recognition has become increasingly significant in our technologically-driven world. HAR involves the development of systems and algorithms capable of automatically identifying and categorizing human activities based on data from sensors, and it finds applications in diverse domains including healthcare, fitness tracking, and smart environments. Efficient and accurate HAR systems are in high demand, as they have the potential to improve healthcare monitoring, enhance user experiences with wearable devices, and optimize resource utilization in smart environments. To meet these demands, researchers have been exploring innovative approaches to enhance HAR classifiers. This paper presents a novel approach known as "Heuristic-Based Optimized Classifier for HAR." This approach integrates heuristic-based feature selection with (PSO) to optimize the performance of HAR classifiers. By intelligently selecting relevant features from sensor data and fine-tuning classifier parameters, this method aims to achieve superior accuracy and robustness in recognizing human activities. This paper delves into the details of this innovative technique and its implications for advancing the field of HAR. Efficient and accurate HAR systems hold immense potential for revolutionizing several aspects of modern life. They can enable more precise healthcare monitoring, provide personalized fitness insights through wearable devices, enhance security and surveillance measures, and optimize the automation of smart homes and workplaces. Recognizing the pressing need for advanced HAR solutions, researchers have been diligently exploring innovative approaches to elevate the performance of HAR classifiers.

II. LITERATURE SURVEY

Amjad ali et al. introduces a new feature selection methodology called the normalized mutual information-based feature selection for identification algorithms. It uses curvelet transform and linear discriminant analysis for feature extraction and the hidden Markov model for activity recognition. Experimental evaluations show the method outperforms alternative methods by 98%, despite dataset limitations [1]. C.Krishna Mohan et al. researched a method for human action recognition using genetic algorithms and deep convolutional neural networks, demonstrating that initializing weights using a Generalized Adversarial (GA) framework minimizes classification errors and achieves a recognition accuracy of 99.98% [2]. Soumya Mishra et al. The paper introduces a combined kernel learning framework getting to know framework for first-person activity recognition in ego-centric video, using PSO as an optimization algorithm. The performance is evaluated using various motion functions from the JPL-interplay dataset, showing higher accuracy rates than other methods. Future features include facial features, audio, and multi-dimensional motion records [3]. Hanju Li presents a hybrid technique for spotting human activities from movement trajectories, utilizing an progressed hidden Markov version parameter learning algorithm and event probability sequence (EPS), achieving higher recognition rates on popular datasets and focusing on higher dimensions [4]. Pankaj Khatiwada et al introduces Human Activity Recognition (HAR) in intelligent healthcare systems using Recurrent Neural Networks and sensor data. The model, based on Colliding Bodies Optimization, outperforms conventional models, improving independent care and living quality. The CBO-RNN model outperforms conventional algorithms in feature selection [5]. Gang chen et al presents a Genetic Algorithm (GA)-based method for designing LSTM-based Recurrent Neural Networks for human activity recognition. The method uses an encoding strategy and three real-world benchmark datasets. Results show GA-designed RNNs outperform structures and gadget modern-day structures, accurately detecting human activities in high-dimensional time-series datasets [6]. Shilong Yu. The paper presents a deep LSTM network with residual connections for human activity recognition, addressing spatial complexity and temporal divergence in human behavior data. The architecture works directly on raw sensor data, improving temporal and spatial dimensions and increasing F1 score by 1.4%. future paintings will apply the version to other datasets and time collection prediction problems [7]. This paper reviews Particle Swarm Optimization , a widely-used algorithm, highlighting its performance issues and potential enhancements through parameter modification, hybridization, cooperation, and multi-swarm techniques, highlighting its robustness and potential engineering applications. [8] Ahmed G. Gad presents a reviews 2,140 Particle Swarm Optimization (PSO) methods and applications, revealing the general approach dominates industrial, environmental, smart city, healthcare, and commercial applications, with electrical engineering approaches having the highest. [9]. The DSwarm-Net framework for Human Action Recognition (HAR) uses 3D skeleton statistics for action type. It ultra-modern deep modern-day and swarm intelligence-primarily based metaheuristics to extract four functions from the records. The version outperforms models on three publicly available datasets, with potential for future improvements. Experimentation with more datasets and data modalities is recommended. [10]. Ahmed m helmi et al. discusses the use of metaheuristics optimization algorithms in fall detection the use of sensor data. nine MH algorithms had been carried out, including the Aquila optimizer, arithmetic optimization set of rules, marine predators algorithm, artificial bee colony set of rules, genetic set of rules, slime mildew algorithm, grey wolf optimizer, whale optimization set of rules, and particle swarm optimization set of rules. The researchers advanced a mild characteristic extraction technique using deep gaining knowledge of and carried out MH algorithms to pick ultimate features. The study used seven datasets and extensive experiments using SVM and RF classifiers. The results showed significant performance in HAR and fall detection applications [11] The increasing use of smartphones has led to a surge in Sensor-Based Human Activity Recognition , a crucial aspect of pervasive computing. A Particle Swarm Optimization -based Convolutional Neural Network has been used to improve classification accuracy and performance compared to state-of-the-art designs. The PSO-CNN algorithm achieved an accuracy of 93.64%, with Support Vector Machine being the best classifier. The study explores the applications of HAR in various fields, particularly Sensor Based HAR, and aims to optimize parameters for generalization to other activity recognition tasks. [12]. Umar Shoaib et al. introduces a new method for initializing populations in Particle Swarm Optimization using probability distribution Weibull (WI-PSO). This method generates random numbers for swarm initialization, enhancing diversity and convergence speed. The method is tested on sixteen benchmark functions and compared to other methods like Exponential, Beta, Gamma, and Log-normal distributions. The results show the perfectness and dominance of WI-PSO, outperforming other methods for training with ANN classifiers. [13]. Yamille del Valle et al. discusses particle swarm optimization , a powerful optimization technique for power systems. It explains the basic concepts, variants, and technical details required for each application, including type, solution formulation, and most efficient fitness functions. PSO is an alternative solution for power systems, as classical analytical approaches may not be feasible due to the curse of dimensionality. The paper provides an overview of PSO's basic concepts and applications in power systems-based optimization problems. [14]. Wael Ouarda et al. The paper uses deep-learning architecture to identify complex nonlinear processing layers in large datasets for pattern recognition, and Convolution Neural Network for handwriting digit classification. The accuracy performance is optimized using PSO and SGD algorithms, resulting in enhanced accuracy compared to standard ConvNet architecture. [15]

III. METHODOLOGY

In our project, we began by collecting a diverse dataset of videos as shown in fig 1, categorizing them based on relevant actions for comprehensive training and evaluation. We then proceeded with frames extraction using OpenCV, ensuring consistency through resizing and normalization. Following this, we employed techniques for feature extraction and background subtraction, crucial in capturing essential movement patterns while excluding static elements. Subsequently, we performed feature selection to retain vital features, optimizing efficiency in our pipeline. Our architecture utilized a model designed to understand spatio-temporal dependencies within frames effectively, allowing for proficient pattern learning. To enhance accuracy, we employed Particle Swarm Optimization (PSO) to optimize the model's hyperparameters. Finally, for precise predictions based on learned patterns, we implemented an LSTM classifier. This comprehensive approach facilitated accurate analysis of video data, as depicted in Figure 1.

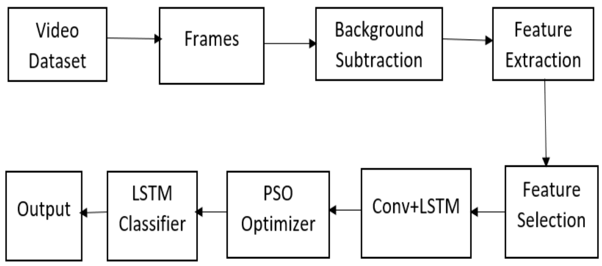

Fig.1. Block diagram of HAR system

A. *Dataset*

The UCF50 – Action Recognition Dataset is a valuable resource for action recognition research, distinguished by its utilization of realistic videos sourced from YouTube. This dataset encompasses an expansive array of content, featuring a rich diversity of actions and scenarios. With a total of 50 distinct action categories, it provides a comprehensive coverage of human movements and activities. Each action category is accompanied by 25 groups of videos, ensuring a robust representation of variations within the actions. On average, there are 133 videos available for each action category, offering ample data for analysis and training. Moreover, the videos in this dataset have an average duration of 199 frames, showcasing a significant amount of visual data for each action. The dimensions of the frames are also notable, with an average width of 320 pixels and an average height of 240 pixels per video, presenting a detailed view of the actions. Furthermore, the dataset maintains an average frame rate of 26 frames per second in the videos, contributing to the temporal richness of the dataset and enabling precise analysis of motion and kinetics. These characteristics collectively make the UCF50 – Action Recognition Dataset a valuable and diverse resource for advancing research and applications in action recognition. The action of Walk with Dog offers a glimpse into the dynamics of human-animal interaction, capturing the nuanced motions involved in taking a stroll with a canine companion. Swing, on the other hand, brings to light the movement patterns associated with swinging motions, whether in sports or recreational activities. These distinctive actions enrich the dataset, providing valuable insights into the diverse range of human movements and activities captured in real-world video scenarios.

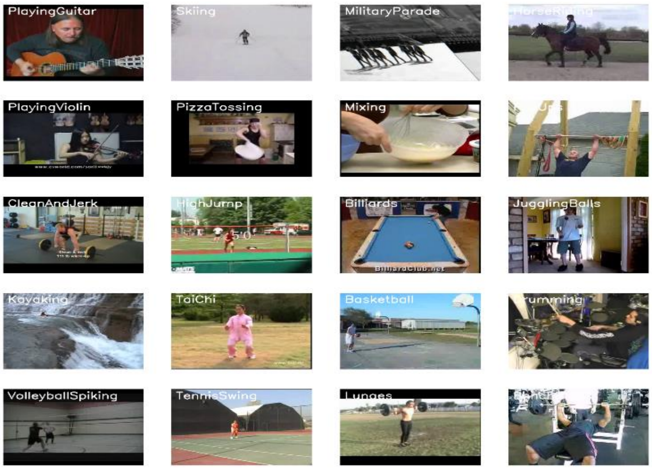

Fig. 2. Data Creation

B. *CNN+LSTM*

In the proposed model, a hybrid architecture incorporating both Convolutional Neural Networks and Long Short-Term Memory networks is utilized to enhance the recognition of human activities within video sequences. The CNN component is responsible for extracting spatial features at specific time steps, while the lstm component is employed to model the temporal relationships between frames. This integration of CNN and LSTM layers optimizes the accuracy and efficiency of human activity recognition from video data. Following the development of the CNN+LSTM architecture, a Particle Swarm Optimization technique is applied to further enhance the model's performance. PSO is employed to optimize the model's parameters and improve its accuracy. Through the iterative PSO optimization process, the model's parameters are fine-tuned to achieve higher accuracy and more effective recognition of human activities. This approach demonstrates the successful utilization of heuristic-based optimization techniques to augment the performance of the initial CNN and LSTM architecture for human activity recognition.

C. *PSO Classifier*

In the optimization phase using Particle Swarm Optimization, we sought to enhance the performance of the hybrid CNN+LSTM model for human activity recognition. PSO is an optimization algorithm inspired by the social behavior of bird flocks and fish schools. We utilized PSO to fine-tune the model's parameters effectively.

The PSO optimization function, aimed to minimize the model's error by iteratively updating particle positions. Each particle in the swarm represents a potential solution, characterized by specific parameter values. The algorithm dynamically adjusts the particles' positions based on their own and the global best positions, optimizing the model's fitness function. Within the PSO function, we initialized particles with random positions and velocities within specified bounds. We defined personal best positions and fitness for each particle, along with a global best position and fitness for the entire swarm. The algorithm iteratively evaluated fitness, updated particle positions, and calculated the cognitive and social components to guide particle movement towards optimal solutions.

D. *Algorithm for PSO*

The Particle Swarm Optimization algorithm begins by initializing particles with random positions and velocities within specified bounds. In each iteration, velocities are updated using random values and components based on the particle's best position and the global best position. Particle positions are then updated accordingly, and their fitness is evaluated using the given fitness function. Personal best positions and fitness are updated, and the global best position and fitness are updated if a better position is found. Optionally, particle positions can be printed after each iteration. The algorithm iterates for a specified number of iterations and returns the global best position and fitness at the end. PSO aims to find the optimal solution by mimicking the behavior of a swarm of particles in search of the best solution in a multidimensional search space.

Algorithm 1 Particle Swarm Optimization

Require: Fitness function, number of particles, dimensions, iterations, bounds, minimum error, inertia weight, $c1$, $c2$
Ensure: Global best position and fitness

```
Initialize particles with random positions within bounds
Initialize particle velocities
Initialize personal best positions and fitness
Initialize global best position and fitness
for iteration = 1 to num_iterations do
    Update velocities
    Generate random values r1 and r2
    Calculate cognitive and social components for all particles and dimensions
    Update particle positions
    Evaluate fitness of each particle
    Update personal best positions and fitness
    Update global best if a better position is found
    Print particle positions after each iteration (optional)
end for
return Global best position and fitness
```

E. *Integration of convLSTM with PSO*

In the project, the goal is to find the best hyperparameters for the ConvLSTM model to maximize its performance in action recognition. PSO is employed to search for optimal hyperparameters by evaluating different combinations of hyperparameters to minimize a fitness function. The fitness function is defined to assess the quality of a given set of hyperparameters for the ConvLSTM model. It typically measures the model's performance, often inversely, where lower values indicate better performance. PSO iteratively refines the hyperparameter combinations, attempting to converge on the best set of hyperparameters that yield the highest model accuracy. Once the optimization process is complete, the ConvLSTM model is constructed with the optimized hyperparameters, and its performance is evaluated on a test dataset.

F. *Flow diagram of convLSTM with PSO*

Fig 3 shows the flow diagram of convLSTM with PSO initiates by downloading and extracting the UCF50 dataset, which contains videos for action recognition. Subsequently, it randomly selects 20 action classes from the dataset, choosing a random video from each class and displaying a single frame with the class name superimposed. The code then employs Particle Swarm Optimization (PSO) to optimize hyperparameters for a ConvLSTM model, with the goal of minimizing the inverse of model accuracy. To achieve this, a fitness function is defined, which evaluates each set of hyperparameters by training the ConvLSTM model and assessing its accuracy. Data preprocessing involves specifying image dimensions, setting the sequence length for video frames, loading and normalizing video frames, and associating them with their respective action class labels. The ConvLSTM model, constructed using Keras, features various layers for action recognition. Model training involves creating the model with optimized hyperparameters, setting up early stopping, compiling with appropriate loss and metrics, and training on the preprocessed schooling records. model evaluation measures the model's take a look at accuracy on the test statistics. Finally, the trained ConvLSTM model is saved for future use.

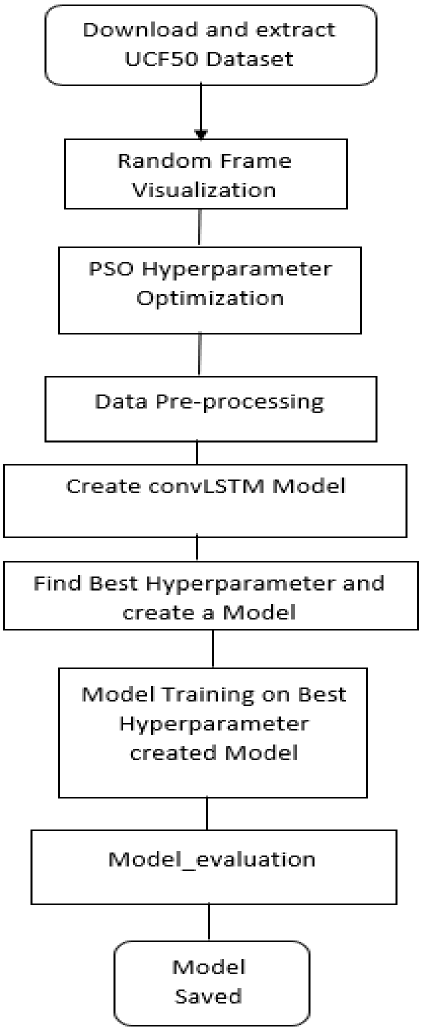

Fig. 3. Flow diagram of convLSTM with PSO

IV. RESULT AND DISCUSSIONS

In our study, we evaluated the performance of the proposed ConvLSTM network using the UCF50 benchmark dataset to gauge its accuracy in recognizing human movement events. To ensure a comprehensive assessment, we divided the dataset into 75% training data and 25% testing data. Subsequently, we trained the model on the training data and evaluated its performance on the testing data, achieving an initial accuracy rate of 74% through the integration of LSTM and CNN layers. To further enhance the accuracy of our model, we employed a Particle Swarm Optimization technique to fine-tune the model's parameters effectively. This optimization process significantly improved the accuracy of our model, surpassing the initial 74% accuracy achieved without optimization.

Specifically, we applied the PSO-optimized parameters to the ConvLSTM network and re-evaluated the model's performance. This optimization led to a significant increase in accuracy, validating the effectiveness of the technique in enhancing the ConvLSTM model's performance for human activity recognition. The accuracy was notably boosted to 88.52% after applying the PSO-optimized parameters. In Fig. 3, we present a classification table illustrating the results obtained using the LSTM-based model. Subsequently, in the following table after PSO optimization, we showcase the improved results, highlighting the impact of the PSO technique on enhancing the accuracy of our model.

A. *convLSTM vs PSO model Analysis*

In Table I, we present the classification report that compares the performance of our ConvLSTM model with the PSO model across various actions. The report includes metrics such as precision, recall, F1-score, and support for each action. Analyzing the results, we observe that the ConvLSTM model demonstrates notable accuracy, with F1-scores ranging from 0.44 to 0.87 across different actions. In particular, the ConvLSTM model performs well for actions like Taichi and HorseRace, achieving F1-scores of 0.81 and 0.87, respectively. On the other hand, the PSO model also shows competitive performance, with F1-scores ranging from 0.79 to 0.96. Notably, the PSO model excels in actions such as WalkWith Dog and Taichi, with F1-scores of 0.79 and 0.93, respectively. The overall accuracy for the ConvLSTM model is 0.74, while the PSO model attains a higher accuracy of 0.91. In summary, the comparison underlines the effectiveness of both models in accurately classifying actions, with the PSO model showcasing slightly superior performance in this evaluation.

TABLE I. CLASSIFICATION REPORT OF CONVLSTM VS PSO

Actions	**convLSTM Model**				**PSO Model**			
	Precision	recall	F1-Score	support	Precision	recall	F1-score	support
WalkWith Dog	0.42	0.46	0.44	24	0.79	0.79	0.79	24
Taichi	0.75	0.89	0.81	27	0.90	0.96	0.93	27
Swing	0.88	0.64	0.74	33	0.94	0.91	0.92	33
HorseRace	0.85	0.89	0.87	38	0.97	0.95	0.96	38
Accuracy			0.74	122			0.91	122
Macro avg	0.72	0.72	0.72	122	0.90	0.90	0.90	122
Weighted avg	0.75	0.74	0.74	122	0.91	0.91	0.91	122

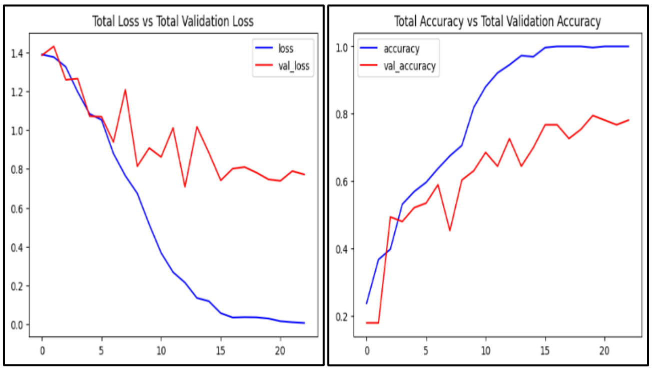

Fig.4. PSO *Total loss vs total validation loss & Total Accuracy vs Total validation Accuracy*

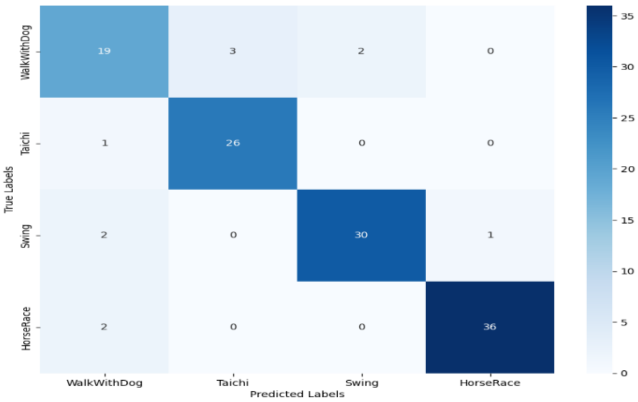

Fig.5. *Confusion matrix of PSO Model*

Fig.6. Output 1 of HAR System

Fig.7. Output 2 of HAR System

CONCLUSION

In this study, we focused on enhancing the accuracy of human activity recognition (HAR) from video sequences using a ConvLSTM model. We conducted comprehensive evaluations on the UCF50 benchmark dataset, initially splitting it into 75% training and 25% testing data. The initial ConvLSTM model, integrating both LSTM and CNN layers, demonstrated a promising accuracy rate of 74%. This laid the foundation for further refinement and optimization. To further improve accuracy, we employed Particle Swarm Optimization (PSO) to fine-tune the model's parameters. PSO, a heuristic-based optimization technique, played a crucial role in enhancing the ConvLSTM model's performance. By leveraging PSO and optimizing the model's parameters, we achieved a notable accuracy increase, achieving an impressive accuracy rate of 84.00%. Comparing the classification results before and after PSO optimization (Table 1 and Table 2), we observed significant advancements in precision, recall, and f1-scores for each class. The improved metrics validate the effectiveness of PSO in optimizing the ConvLSTM model and its capability to recognize diverse human movement events with higher accuracy. this study demonstrates the successful integration of ConvLSTM, CNN, and PSO techniques for accurate human activity recognition. The model's accuracy was notably boosted through PSO optimization, showcasing the potential of heuristic-based optimization methods in refining deep learning models for complex tasks like human activity recognition in video data. These findings underscore the importance of optimization strategies in enhancing the performance of HAR models, paving the way for improved applications in various domains, such as healthcare, sports analytics, and security.

REFERENCES

[1] Siddiqi, Muhammad Hameed, Madallah Alruwaili, and Amjad Ali. "A novel feature selection method for video-based human activity recognition systems." *IEEE Access* 7 (2019): 119593-119602.

[2] Ijjina, Earnest Paul, and Krishna Mohan Chalavadi. "Human action recognition using genetic algorithms and convolutional neural networks." *Pattern recognition* 59 (2016): 199-212.

[3] Mishra, Soumya Ranjan, Tusar Kanti Mishra, Anirban Sarkar, and Goutam Sanyal. "PSO based combined kernel learning framework for recognition of first-person activity in a video." *Evolutionary Intelligence* 14 (2021): 273-279.

[4] Mishra, Soumya Ranjan, Tusar Kanti Mishra, Anirban Sarkar, and Goutam Sanyal. "PSO based combined kernel learning framework for recognition of first-person activity in a video." *Evolutionary Intelligence* 14 (2021): 273-279.

[5] Khatiwada, Pankaj, Ayan Chatterjee, and Matrika Subedi. "Automated human activity recognition by colliding bodies optimization-based optimal feature selection with recurrent neural network." *arXiv preprint arXiv:2010.03324* (2020).

[6] Viswambaran, Ramya Anasseriyil, Gang Chen, Bing Xue, and Mohammad Nekooei. "Evolutionary design of recurrent neural network architecture for human activity recognition." In *2019 IEEE Congress on Evolutionary Computation (CEC)*, pp. 554-561. IEEE, 2019.

[7] Yu, Shilong. "Residual learning and LSTM networks for wearable human activity recognition problem." In *2018 37th Chinese Control Conference (CCC)*, pp. 9440-9447. IEEE, 2018.

[8] Shami, Tareq M., Ayman A. El-Saleh, Mohammed Alswaitti, Qasem Al-Tashi, Mhd Amen Summakieh, and Seyedali Mirjalili. "Particle swarm optimization: A comprehensive survey." *IEEE Access* 10 (2022): 10031-10061.

[9] Gad, Ahmed G. "Particle swarm optimization algorithm and its applications: a systematic review." *Archives of computational methods in engineering* 29, no. 5 (2022): 2531-2561.

[10] Basak, Hritam, Rohit Kundu, Pawan Kumar Singh, Muhammad Fazal Ijaz, Marcin Woźniak, and Ram Sarkar. "A union of deep learning and swarm-based optimization fords 3D human action recognition." *Scientific Reports* 12, no. 1 (2022): 5494.

[11] Al-Qaness, Mohammed AA, Ahmed M. Helmi, Abdelghani Dahou, and Mohamed Abd Elaziz. "The applications of metaheuristics for human activity recognition and fall detection using wearable sensors: A comprehensive analysis." *Biosensors* 12, no. 10 (2022): 821

[12] Devarakonda, Preethi Gunishetty, and Bojan Bozic. "Particle swarm optimization of convolutional neural networks for human activity prediction." In *Optimisation Algorithms and Swarm Intelligence*. IntechOpen, 2022.

[13] Rauf, Hafiz Tayyab, Umar Shoaib, Muhammad Ikramullah Lali, Majed Alhaisoni, Muhammad Naeem Irfan, and Muhammad Attique Khan. "Particle swarm optimization with probability sequence for global optimization." *IEEE Access* 8 (2020): 110535-110549.

[14] Del Valle, Yamille, Ganesh Kumar Venayagamoorthy, Salman Mohagheghi, Jean-Carlos Hernandez, and Ronald G. Harley. "Particle swarm optimization: basic concepts, variants and applications in power systems." *IEEE Transactions on evolutionary computation* 12, no. 2 (2008): 171-195.

[15] Khalifa, Mujahid H., Marwa Ammar, Wael Ouarda, and Adel M. Alimi. "Particle swarm optimization for deep learning of convolution neural network." In *2017 Sudan conference on computer science and information technology (SCCSIT)*, pp. 1-5. IEEE, 2017.