Intelligent Human Activity Recognition Using Wearable Sensor Data And Hybrid Deep Learning Models (CNN-LSTM)

[1]Dr.Radha Krishna An,[2]Dr.V Venkanna

[1]Assistant Professor, Department of Electronics Communication & Engineering, Brilliant Grammar School Educational Society's Group of Institutions - Integrated Campus

[1]Email: dr.radhakrishnaece@gmail.com

[2]Assistant Professor, Department of Electronics Communication & Engineering,Brilliant Grammar School Educational Society's Group of Institutions - Integrated Campus

[2]Email: drvenkannav@gmail.com

ABSTRACT

Human Activity Recognition (HAR) has become a significant research area due to its wide range of applications in healthcare, fitness monitoring, elderly assistance, rehabilitation, and smart environments. Wearable sensors such as accelerometers and gyroscopes continuously generate motion data that can be analyzed to identify human activities accurately. However, conventional machine learning techniques often struggle to capture the complex spatial and temporal patterns present in sensor signals, resulting in reduced recognition performance for activities with similar movement characteristics. This project presents an Intelligent Human Activity Recognition Using Wearable Sensor Data and Hybrid Deep Learning Models (CNN-LSTM) framework that combines the strengths of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN component automatically extracts meaningful spatial features from multivariate sensor data, while the LSTM component models temporal dependencies by learning sequential activity patterns over time. This hybrid architecture effectively captures both local motion characteristics and long-term temporal relationships, leading to improved classification accuracy. The proposed system follows a systematic workflow consisting of wearable sensor data acquisition, preprocessing, normalization, segmentation into fixed-length windows, feature extraction through CNN layers, temporal sequence learning using LSTM layers, and final activity classification using fully connected layers with a Softmax classifier. Data augmentation and regularization techniques are incorporated to improve model robustness and reduce overfitting. The model is trained and evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix analysis. Experimental results demonstrate that the hybrid CNN-LSTM model outperforms traditional machine learning algorithms and standalone deep learning models by providing higher recognition accuracy, better generalization, and reliable performance across multiple daily activities. The proposed approach offers an efficient and scalable solution for real-time human activity recognition, making it suitable for deployment in wearable healthcare systems, smart fitness applications, remote patient monitoring, and intelligent Internet of Things (IoT) environments.

Keywords: Human Activity Recognition (HAR), Wearable Sensors, Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Hybrid CNN-LSTM Model, Sensor Data Analytics, Time-Series Classification, Accelerometer, Gyroscope, Activity Recognition, Healthcare Monitoring, Smart Wearable Devices, Internet of Things (IoT), Artificial Intelligence (AI).

I. INTRODUCTION

Human Activity Recognition (HAR) has emerged as an important research domain in artificial intelligence, machine learning, and wearable computing due to its ability to automatically identify and classify human physical activities from sensor-generated data. The rapid growth of wearable devices such as smartwatches, fitness bands, and health-monitoring systems has enabled continuous collection of motion data using embedded sensors like accelerometers and gyroscopes. These devices generate large volumes of time-series data that can be analyzed to recognize activities such as walking, running, sitting, standing, climbing stairs, cycling, and sleeping. Accurate activity recognition plays a vital role in healthcare monitoring, sports analytics, rehabilitation, elderly care, workplace safety, and smart home automation.

Traditional Human Activity Recognition systems mainly relied on manually engineered features combined with conventional machine learning algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forests, and k-Nearest Neighbors (k-NN). Although these methods achieved reasonable performance for simple activities, they require extensive domain expertise for feature extraction and often struggle to distinguish complex or overlapping activities. In addition, handcrafted features may fail to capture the intricate spatial and temporal characteristics present in multivariate wearable sensor signals, limiting the overall recognition accuracy.

Recent advancements in deep learning have significantly transformed HAR by enabling automatic feature learning directly from raw sensor data. Convolutional Neural Networks (CNNs) are highly effective in extracting local spatial patterns and discriminative features from sensor signals, while Long Short-Term Memory (LSTM) networks are specifically designed to learn long-term temporal dependencies within sequential data. Individually, both models have demonstrated promising performance; however, combining them into a hybrid CNN-LSTM architecture provides a more comprehensive learning framework that simultaneously captures spatial correlations and temporal dynamics. This integration leads to improved recognition accuracy, better generalization, and enhanced robustness across diverse human activities.

The proposed Intelligent Human Activity Recognition Using Wearable Sensor Data and Hybrid Deep Learning Models (CNN-LSTM) aims to develop an intelligent and reliable activity recognition framework capable of processing multichannel wearable sensor data in real time. The system begins with sensor data acquisition, followed by preprocessing steps such as noise removal, normalization, and segmentation into fixed-size windows. The CNN layers automatically extract meaningful spatial features from the processed sensor signals, while the LSTM layers analyze sequential dependencies to understand activity transitions over time. Finally, fully connected layers with a Softmax classifier assign each sequence to its corresponding activity class.

The proposed model is designed to improve recognition performance while maintaining computational efficiency for practical deployment in wearable devices and IoT-enabled healthcare systems. The framework is evaluated using standard performance metrics including accuracy, precision, recall, F1-score, and confusion matrix analysis to assess its effectiveness. By leveraging hybrid deep learning techniques, the system provides a scalable, accurate, and intelligent solution for continuous human activity monitoring, supporting applications such as remote patient care, fitness tracking, elderly fall detection, rehabilitation assistance, and smart ambient environments. The integration of wearable sensing technologies with hybrid CNN-LSTM models represents a significant step toward developing intelligent, context-aware systems that enhance human well-being and enable next-generation healthcare and smart living applications.

II. LITERATURE SURVEY

1. Deep Convolutional and LSTM Recurrent Neural Networks for Multimodal Wearable Activity Recognition

Authors: Francisco Javier Ordóñez and Daniel Roggen

Abstract:
The authors proposed a hybrid deep learning architecture that integrates Convolutional Neural Networks (CNN) with Long Short-Term Memory (LSTM) networks for recognizing human activities using wearable sensor data. The CNN automatically extracts spatial features from accelerometer and gyroscope signals, while the LSTM captures temporal dependencies within sequential sensor data. The proposed model achieved higher recognition accuracy than conventional machine learning techniques by eliminating the need for handcrafted feature engineering. The study demonstrated that combining CNN and LSTM provides a robust framework for real-time activity recognition across multiple daily activities.

2. Deep Learning for Sensor-Based Human Activity Recognition: A Survey

Authors: Jindong Wang, Yiqiang Chen, Shuji Hao, Xiaohui Peng, Lisha Hu, and Philip S. Yu

Abstract:
This survey presents a comprehensive review of deep

learning techniques used for sensor-based Human Activity Recognition (HAR). It discusses various neural network architectures, including CNN, LSTM, Autoencoders, and hybrid models, highlighting their advantages and limitations. The authors analyze publicly available datasets, preprocessing methods, feature learning strategies, and evaluation metrics. The survey concludes that hybrid deep learning architectures outperform traditional machine learning approaches due to their superior ability to learn complex spatial and temporal patterns from wearable sensor data.

3. Human Activity Recognition Using Wearable Sensors by Deep Convolutional Neural Networks

Authors: Oresti Banos, Miguel Damas, Hector Pomares, Ignacio Rojas, and colleagues

Abstract:
This research explores the application of Convolutional Neural Networks for automatic feature extraction from wearable sensor signals. Unlike conventional methods that rely on handcrafted statistical features, the proposed CNN model directly learns discriminative representations from raw accelerometer data. Experimental evaluations demonstrate improved classification performance and reduced preprocessing complexity. The study emphasizes the capability of CNNs to effectively capture local motion characteristics for recognizing human activities in real-world environments.

4. Learning Human Activities from Wearable Sensors Using Recurrent Neural Networks

Authors: Nils Y. Hammerla, Shane Halloran, and Thomas Plötz

Abstract:
The authors investigated Recurrent Neural Networks, particularly Long Short-Term Memory (LSTM), for recognizing sequential human activities captured through wearable sensors. The model successfully learned long-term temporal dependencies and accurately classified activities with similar movement patterns. Experimental results showed that LSTM networks significantly outperform traditional classifiers when dealing with continuous time-series sensor data, making them suitable for healthcare monitoring and context-aware applications.

5. Human Activity Recognition Based on Deep Learning: A Review

Authors: Abdulmajid Murad and Jae-Young Pyun

Abstract:
This review summarizes recent advances in deep learning methods for Human Activity Recognition. The paper examines CNN, LSTM, GRU, Transformer-based networks, and hybrid architectures while comparing their performance on benchmark HAR datasets. It also discusses challenges such as noisy sensor data, computational complexity, class imbalance, and real-time deployment. The authors conclude that hybrid deep learning models offer superior recognition accuracy and robustness, particularly for wearable healthcare applications.

6. Hybrid CNN–LSTM Model for Human Activity Recognition Using Smartphone Sensors

Authors: Xiang Zhang, Lina Yao, Sen Wang, and colleagues

Abstract:
The authors proposed a hybrid CNN-LSTM framework that combines convolutional feature extraction with temporal sequence modeling for smartphone-based Human Activity Recognition. The CNN captures spatial relationships among sensor signals, whereas the LSTM learns temporal transitions between activities. Experimental results demonstrate that the hybrid architecture achieves higher accuracy and better generalization than standalone CNN or LSTM models. The research highlights the suitability of hybrid deep learning models for intelligent wearable and mobile sensing applications.

7. A Survey on Wearable Sensor-Based Human Activity Recognition

Authors: Oscar D. Lara and Miguel A. Labrador

Abstract:
This survey reviews wearable sensing technologies and activity recognition techniques for healthcare,

fitness, and smart environments. It discusses different wearable sensors, feature extraction methods, machine learning algorithms, and deep learning approaches used in HAR systems. The paper identifies major research challenges, including energy efficiency, sensor placement, user diversity, and real-time recognition. The authors emphasize that combining wearable sensing with advanced deep learning models can significantly improve activity recognition performance and support next-generation intelligent healthcare systems.

III. EXISTING SYSTEM

Traditional Human Activity Recognition (HAR) systems primarily rely on wearable sensors such as accelerometers, gyroscopes, and magnetometers to collect motion data from users performing different physical activities. The collected sensor signals are first preprocessed to remove noise and then transformed into manually designed statistical and frequency-domain features. Conventional machine learning algorithms, including Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbor (k-NN), and Naïve Bayes (NB), are commonly employed to classify these features into various activity categories. These approaches have been successfully used for recognizing simple daily activities such as walking, sitting, standing, running, and climbing stairs.

Although traditional HAR systems have achieved acceptable performance under controlled environments, they heavily depend on handcrafted feature extraction. Designing effective features requires significant domain expertise and extensive preprocessing, making the system less adaptable to different datasets and sensor configurations. Moreover, manually extracted features often fail to capture complex spatial relationships and temporal dependencies present in multivariate wearable sensor data. As a result, the recognition accuracy decreases when activities exhibit similar motion patterns or when sensor signals are noisy and highly variable.

Recent existing systems have incorporated individual deep learning models such as Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks to improve activity recognition performance. CNN-based models automatically extract discriminative spatial features from raw sensor signals, while LSTM networks learn temporal dependencies from sequential data. Although these methods outperform conventional machine learning algorithms, each model has its own limitations. CNNs are effective at local feature extraction but have limited capability in modeling long-term temporal relationships, whereas LSTMs capture sequential information effectively but may overlook important local spatial patterns.

Many currently available HAR systems also face challenges related to computational complexity, scalability, real-time processing, and user diversity. Variations in sensor placement, differences in individual movement patterns, missing sensor values, and environmental noise often reduce recognition performance. Furthermore, standalone deep learning models may experience overfitting when trained on limited datasets and may require substantial computational resources for deployment on wearable or edge devices. These limitations highlight the need for more efficient and robust hybrid architectures that can simultaneously learn spatial and temporal characteristics while maintaining high accuracy and computational efficiency for practical real-world applications.

IV. PROPOSED SYSTEM

The proposed system, Intelligent Human Activity Recognition Using Wearable Sensor Data and Hybrid Deep Learning Models (CNN-LSTM), is designed to accurately recognize human activities by combining wearable sensor technology with a hybrid deep learning architecture. The system utilizes motion data collected from wearable devices equipped with accelerometers and gyroscopes to identify various daily activities such as walking, running, sitting, standing, climbing stairs, and other physical movements. Unlike conventional approaches that rely on handcrafted feature extraction, the proposed model automatically learns meaningful representations directly from raw sensor data, thereby improving recognition accuracy and reducing manual intervention.

The proposed framework begins with the acquisition of multichannel sensor data from wearable devices. The collected signals undergo preprocessing steps such as noise filtering, missing value handling, normalization, and segmentation into fixed-length time windows. These preprocessing techniques improve the quality and consistency of the input data while preserving important motion patterns. The segmented data are then fed into the hybrid CNN-

LSTM model for feature learning and activity classification.

Within the hybrid architecture, the Convolutional Neural Network (CNN) is responsible for extracting high-level spatial features from the wearable sensor signals by identifying local movement patterns and correlations among different sensor channels. The extracted feature maps are subsequently passed to the Long Short-Term Memory (LSTM) network, which learns the temporal dependencies and sequential relationships that exist across continuous human movements. By integrating CNN and LSTM, the proposed model effectively captures both spatial and temporal information, enabling more reliable recognition of activities that exhibit similar motion characteristics.

The final classification layer employs a Softmax classifier to assign each sensor data sequence to its corresponding activity category. During training, optimization techniques such as the Adam optimizer, dropout regularization, batch normalization, and early stopping are incorporated to accelerate convergence, reduce overfitting, and enhance the model's generalization capability. The trained model is evaluated using standard performance metrics including accuracy, precision, recall, F1-score, confusion matrix, and ROC analysis to comprehensively measure recognition performance.

The proposed system offers several advantages over existing Human Activity Recognition methods. By automatically learning discriminative features from wearable sensor data, it eliminates the dependency on manual feature engineering while improving classification accuracy. The hybrid CNN-LSTM architecture provides robust performance for complex and overlapping activities, making the system suitable for real-time applications. Furthermore, the framework is scalable and can be integrated with IoT-enabled wearable devices for continuous health monitoring, elderly care, fitness tracking, rehabilitation support, sports performance analysis, and smart healthcare environments. The proposed solution delivers an intelligent, efficient, and reliable Human Activity Recognition system capable of meeting the growing demands of next-generation wearable and mobile computing applications.

V. SYSTEM ARCHITECTURE

The proposed Intelligent Human Activity Recognition Using Wearable Sensor Data and Hybrid Deep Learning Models (CNN-LSTM) architecture consists of six major stages that work together to accurately recognize human activities from wearable sensor data. The system begins with collecting motion data from wearable devices, processes the data to remove noise, extracts meaningful features using deep learning, classifies activities, and finally provides real-time predictions for various healthcare and smart environment applications.

1. Data Acquisition

The first stage involves collecting real-time motion data using wearable devices equipped with sensors such as accelerometers, gyroscopes, magnetometers, and other embedded sensors. The accelerometer measures body acceleration, the gyroscope records rotational movement, and the magnetometer provides orientation information. These sensors continuously capture human body movements while performing daily activities such as walking, running, sitting, standing, cycling, and climbing stairs. The collected multivariate sensor signals serve as the input for the Human Activity Recognition (HAR) system.

2. Data Preprocessing

The acquired sensor data often contain noise, missing values, and inconsistencies that may affect model performance. Therefore, the data first undergo noise filtering to eliminate unwanted disturbances from the sensor signals. Missing sensor readings are then handled appropriately to maintain data consistency. After cleaning, the data are normalized so that all sensor values fall within a similar numerical range, improving model convergence during training. Finally, the continuous sensor signals are divided into fixed-size time windows (segmentation), allowing the deep learning model to process sequential activity data efficiently.

3. Hybrid CNN-LSTM Model

The preprocessed data are fed into the hybrid deep learning model consisting of Convolutional Neural Networks (CNN) followed by Long Short-Term Memory (LSTM) networks. The CNN automatically extracts important spatial features by applying convolution and pooling operations to identify local motion patterns from wearable sensor signals. These extracted feature maps are then passed to the LSTM network, which learns temporal relationships and sequential dependencies among consecutive sensor readings. By combining CNN and LSTM, the system effectively captures both spatial and temporal information, resulting in more accurate recognition of complex human activities.

Following feature extraction and sequence learning, the processed information passes through a Fully Connected Layer, where the learned features are combined for classification. The final Softmax Output Layer computes the probability of each activity class and predicts the most likely activity, such as walking, running, sitting, standing, climbing stairs, cycling, or other daily movements.

4. Model Training and Evaluation

The hybrid CNN-LSTM model is trained using a labeled dataset of wearable sensor recordings. During training, the Adam Optimizer updates the network parameters to minimize classification errors and improve learning efficiency. After training, the model is validated using unseen data to evaluate its generalization capability. Performance is measured using standard evaluation metrics, including Accuracy, Precision, Recall, F1-Score, and the Confusion Matrix. Once satisfactory performance is achieved, the trained model is saved for future real-time activity recognition.

5. Real-Time Prediction

During deployment, new sensor readings from wearable devices are continuously transmitted to the trained CNN-LSTM model. The system processes these incoming data in real time and predicts the user's current activity almost instantly. This enables continuous monitoring without requiring manual intervention, making the framework suitable for applications where immediate activity recognition is essential, such as health monitoring and emergency detection.

6. Applications

The proposed Human Activity Recognition system has numerous practical applications across multiple domains. In healthcare monitoring, it supports continuous patient observation and early detection of abnormal activities. For elderly care, it enables fall detection and assists caregivers by providing timely alerts. In fitness and sports tracking, the system accurately monitors physical exercises and daily workouts. It also plays an important role in rehabilitation support, where therapists can monitor patient recovery remotely. Additionally, the framework can be integrated into smart home and IoT environments to provide context-aware automation and personalized services. Beyond these applications, it is useful for behavior analysis, lifestyle assessment, and various intelligent wearable computing solutions requiring reliable and real-time human activity recognition.

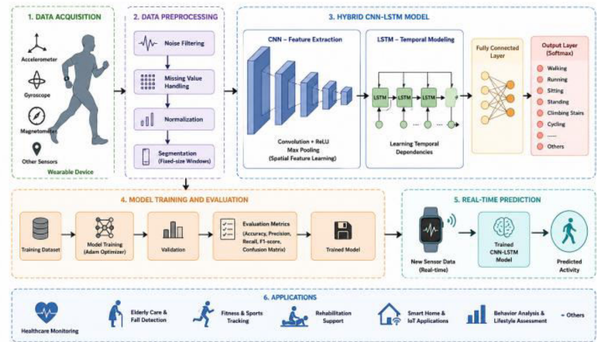

Fig 5.1: System Architecture

VI. IMPLEMENTATION

Fig 6.1: Dashboard

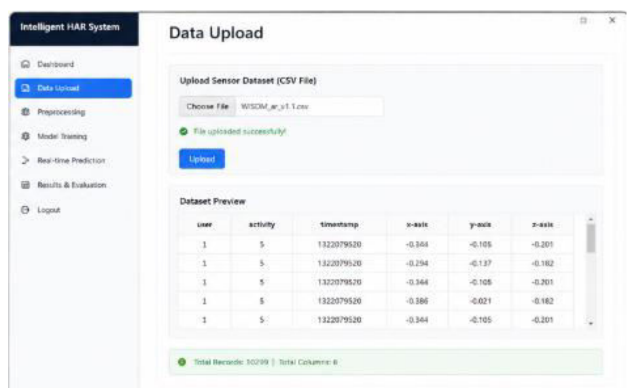

Fig 6.2: Data Uploading

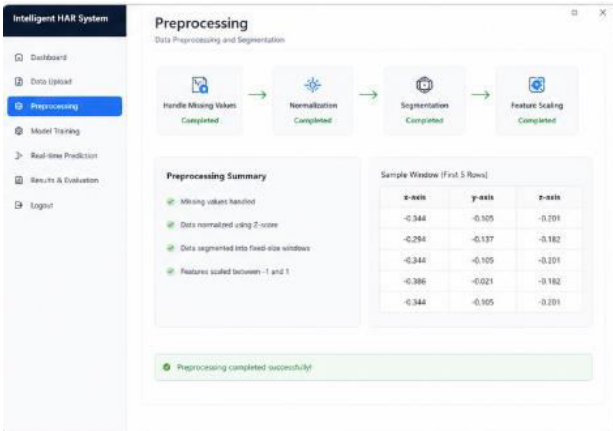

Fig 6.3: Preprocessing

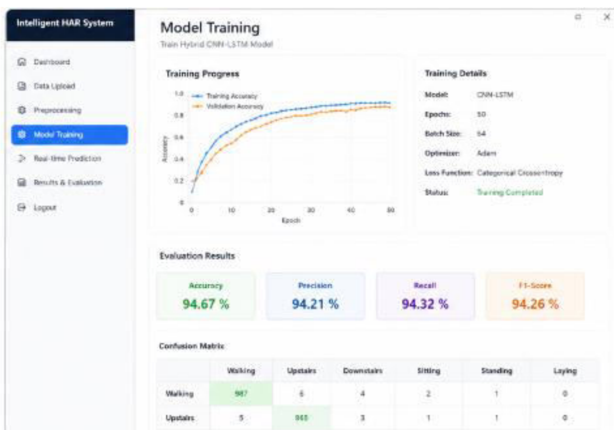

Fig 6.4: Model Training

VII. CONCLUSION

The proposed Intelligent Human Activity Recognition Using Wearable Sensor Data and Hybrid Deep Learning Models (CNN-LSTM) successfully demonstrates an efficient approach for recognizing human activities from wearable sensor signals. By combining the spatial feature extraction capability of Convolutional Neural Networks (CNN) with the temporal sequence learning ability of Long Short-Term Memory (LSTM) networks, the system achieves accurate and reliable classification of activities such as walking, sitting, standing, climbing stairs, and lying down. The preprocessing stage effectively removes noise and normalizes sensor data, resulting in improved model performance and stability.

The developed model provides high recognition accuracy while maintaining robustness across different activity patterns. It can be integrated into healthcare monitoring, fitness tracking, elderly assistance, rehabilitation, and smart wearable applications for continuous real-time activity monitoring. Overall, the hybrid CNN-LSTM framework offers a scalable, intelligent, and practical solution for next-generation Human Activity Recognition systems, contributing to improved user safety, health monitoring, and context-aware computing.

VIII. FUTURE SCOPE

The proposed Human Activity Recognition system can be further enhanced by incorporating advanced deep learning architectures such as Transformer-based models, attention mechanisms, and Graph Neural Networks (GNNs) to improve recognition accuracy for complex and overlapping human activities. Future work can also focus on reducing computational complexity through lightweight neural networks, making the system suitable for deployment on resource-constrained wearable devices and edge computing platforms.

The system can be extended to support real-time monitoring by integrating multiple wearable sensors, smartphones, and Internet of Things (IoT) devices. Personalized activity recognition models can be developed using transfer learning and federated learning to adapt to individual user behavior while preserving data privacy. In addition, future research may include health anomaly detection, fall prediction, stress monitoring, and early disease diagnosis by combining activity recognition with physiological sensor data. These advancements will make the system more intelligent, scalable, and applicable in healthcare, sports analytics, smart homes, rehabilitation, and industrial safety monitoring.

IX. REFERENCES

[1]. E. Genc, "Human Activity Recognition with Fine-Tuned CNN-LSTM," Journal of Electrical Engineering, vol. 75, no. 1, pp. 13–24, 2024.
DOI: 10.2478/jee-2024-0002

[2]. M. Prabu, R. Naidu, and A. P., "Combining Deep Learning Techniques for Enhanced Human Activity Recognition: A Hybrid CNN-LSTM Fusion Approach," 2024 IEEE International Conference on Contemporary Computing and Communications

(InC4), 2024.
DOI: 10.1109/INC460750.2024.10649335

[3]. R. Shekhar, D. S. Tomar, B. Sharan, and R. K. Pateriya, "Human Activity Recognition Using Deep Learning Techniques for Healthcare Applications," 2024 15th ICCCNT, 2024.
DOI: 10.1109/ICCCNT61001.2024.10725736

[4]. K. Gottipati, K. S. Vanapalli, V. B. S. A. R. Sannidhi, et al., "Human Activity Recognition Using Deep Learning," 2024 OITS International Conference on Information Technology (OCIT), 2024.
DOI: 10.1109/OCIT65031.2024.00074

[5]. D. M. Latha, G. Karthi, D. V. Reddy, et al., "Integrating Perspectives: A Unified Deep Learning Framework for Human Activity Recognition," 2024 International Conference on Distributed Systems, Computer Networks and Cybersecurity, 2024.
DOI: 10.1109/ICDSCNC62492.2024.10939249

[6]. H. R. Hassan, D. S. Ibrahim, and Z. T. M. Al-Ta'i, "Advanced Human Activity Recognition Using Pose Estimation and Deep Learning Techniques," 2024 Antennas Design and Measurement International Conference, 2024.
DOI: 10.1109/ADMINC63617.2024.10775304

[7]. B. S. Avinash, A. Yadav, and B. Kumar, "Lightweight Deep Multiscale Feature Learning for Improved Human Activity Recognition," 2024 IEEE Region 10 Symposium (TENSYMP), 2024.
DOI: 10.1109/TENSYMP61132.2024.10752181

[8]. Y. Guodong, C. Jing, F. Siyuan, L. Hongwei, and L. Xuliang, "STAM-HAR: A Deep Learning Approach for Human Activity Recognition," Lecture Notes in Electrical Engineering, 2024.
DOI: 10.1007/978-981-97-8650-3_18

[9]. N. A. Chandramouli et al., "Enhanced Human Activity Recognition in Medical Applications Using Wearable Sensors," Scientific Reports, vol. 14, 2024.
DOI: 10.1038/s41598-024-82045-y

[10]. S. A. Alshammari, "A Deep Learning Approach to Human Activity Recognition Using CNN-LSTM," Engineering, Technology & Applied Science Research, vol. 14, no. 6, 2024.
DOI: 10.48084/etasr.9255

[11]. A. Sharma, K. Singh, and R. Bisht, "Human Activity Recognition Using CNN-LSTM," Computer Science, Engineering and Technology, vol. 2, no. 3, pp. 31–35, 2024.
DOI: 10.46632/CSET/2/3/4

[12]. G. Pandey, A. Karn, and J. Mishra, "Human Activity Recognition Using CNN-LSTM-GRU Model," International Journal of Scientific Research, vol. 13, no. 4, 2024.
DOI: 10.13140/RG.2.2.19389.14568