Humanactivity Recognition using Deep Learning

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Abstract
Human activity recognition (HAR) plays a crucial role in various fields, including healthcare, surveillance, and human-computer interaction. This study explores the application of deep learning techniques for accurate and efficient human activity recognition. Leveraging the capabilities of deep neural networks, specifically convolutional neural networks (CNNs) and recurrent neural networks (RNNs), the proposed approach aims to capture both spatial and temporal features from sensor data. The dataset utilized in this research comprises multi-model sensor inputs, such as accelerometer and gyroscope readings, collected from wearable devices. The deep learning model is designed to automatically learn hierarchical representations of the raw sensor data, enabling robust feature extraction and discrimination between different human activities. Transfer learning is employed to enhance model generalization across diverse activity categories and varying sensor setups. Experimental evaluations are conducted on real-world datasets, demonstrating the effectiveness of the proposed deep learning framework in accurately classifying activities, including walking, running, sitting, and standing. Comparative analyses against traditional machine learning methods underscore the superior performance and adaptability of deep learning in handling complex and dynamic activity patterns. The results showcase the potential of deploying deep learning models in real-time human activity recognition systems, highlighting their scalability and efficiency. The study contributes to the advancement of HAR methodologies, paving the way for the development of more reliable and robust systems in applications such as healthcare monitoring, assisted living, and smart environments.

Keywords: Recurrent Neural Networks, Deep Learning, Convolutional Neural Networks, Attention Mechanisms, Transfer Learning, Dataset Pre-Processing.

Introduction

Human Deep learning-based activity recognition cutting-edge at the intersection of artificial intelligence and human-computer interaction that aims to automatically identify and classify activities performed by individuals based on sensor data. By leveraging specifically, researchers developers patterns and from sensory input accelerometer and gyroscope data from wearable devices or video feeds, allowing for accurate real-time activity recognition. This technology has wide-ranging healthcare, sports performance analysis, security monitoring, and labelled these systems learn complex temporal and spatial relationships in the data, enabling them to recognize a diverse set of human activities with high precision, using deep learning continues to evolve rapidly, with ongoing research focusing on improving the robustness and generalizability of models, enhancing interpretability, and exploring new sensor modalities techniques enhance and efficiency of activity recognition systems. As advancements in hardware and software continue to empower deeper and more efficient neural networks, the capabilities of human activity recognition systems are poised to revolutionize various industries and enable innovative applications that can enhance human wellbeing and performance in both personal and professional settings.

Recent Works

Human activity identification has attracted a lot of attention recently in the literature, with an emphasis on multimodal techniques that emphasize classification, applications, problems, and future possibilities. Yadav, Tiwari, Pandey, and Akbar (2021) conducted a thorough review in this area, illuminating important facets of the subject. Furthermore, Ferrari, Micucci, Mobilio, and Napoletano (2021) clarified developments and applications by investigating the changing patterns of human activity recognition utilizing cellphones. Similarly, Xu and Qiu (2021) demonstrated the potential of convolutional neural networks by exploring embedded applications and human activity recognition. Additionally, presenting a novel viewpoint, Ronald, Poulose, and Han (2021) unveiled the iSPLInception architecture, a customized deep learning approach for identifying human behavior. With a focus on recent advancements, Zhang, Li, Shahabi, and colleagues provided examinations in wearable sensor-based identification of human activity in 2022. Chen, Zhang, Yao, and others presented an overview of human movement via in 2021 and talked about the challenges and potential that come with it. In sensor-based human activity detection with spatio-temporal deep learning by Nafea, Abdul, Muhammad, and Alsulaiman (2021), the significance of temporal dynamics was highlighted. In addition, Gu, Chung, Chignell, and colleagues conducted a study of deep learning techniques in 2021; the survey included insights on recent developments and applications. Mekruksavanich and Jitpattanakul (2021) conducted a study on wearable sensor-based detection, highlighting the possibility of enhancing accuracy through deep learning models. Last but not least, Ramanujam, Perumal, and Padmavathi's analysis of this using wearables in 2021 emphasized the significance of deep learning approaches in enhancing recognition performance and accuracy.

Proposed Methodology

The proposed system for Human Activity Recognition (HAR) using deep learning represents an innovative approach to advance the accuracy and efficiency of activity recognition models.

This system introduces a hybrid architecture that seamlessly integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), aiming to capture both spatial and temporal features from multimodal sensor data. The CNN component focuses on extracting intricate spatial patterns, enabling the recognition of static and dynamic activities, while the RNN component, employing Long Short-Term Memory (LSTM) networks, models temporal dependencies to decipher nuanced activity patterns evolving over time. In order to enhance adaptability and generalization, the system incorporates transfer learning, fine-tuning pre-trained models for the specific task of human activity recognition. Real-time processing is prioritized through optimizations to streamline the inference process, ensuring low-latency recognition of activities critical for applications such as healthcare monitoring. Additionally, attention mechanisms are explored to refine the model's focus on relevant spatiotemporal cues, contributing to improved discriminative capabilities.The proposed system undergoes comprehensive evaluation on diverse real- world datasets, employing standard metrics to assess its performance and validate its potential for practical deployment in healthcare, sports monitoring, and smart environments.

Deep Learning

Human Deep learning-based activity recognition involves leveraging advanced. These models extract meaning ful patterns from sensory input, allowing for accurate real-time recognition. Combining CNNs and RNNs into hybrid models captures both spatial and temporal, information, enhancing performance. Attention mechanisms, utilizes pre-trained for efficient training on smaller datasets. These advancements hold promise.

Proposed Methodology Architecture

The proposed approach presented in Figure 2. depicted in the image outlines pipeline from image. Preprocessing is the first step, optimizing the images for the model. The data is then partitioned, and the target classes for activity recognition are identified. A division into training and test sets follows. The model is built using a combination of machine learning techniques, possibly including ensemble methods and hyperparameter tuning, to enhance performance. Cross-validation methods are applied to ensure robustness. Finally, the validated model is tested and deployed for activity recognition tasks.

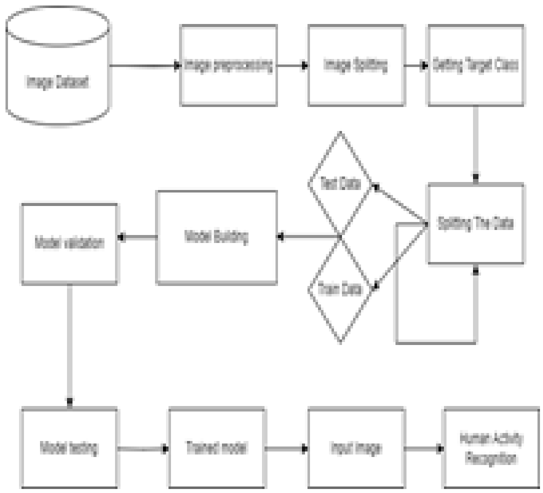

Figure 1 Proposed System Architecture

Evaluation Parameter

Performance evaluation encompasses various factors, with parameters designed to assess how effectively the model classifies different activities based on input data.

Key evaluation metrics include the F1-score, recall, accuracy, precision, and specificity. These metrics offer insights into the model's performance across diverse activity types.

Accuracy serves as a measure of the model's overall predictive accuracy, considering its predictions for True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

It is calculated using the formula:

Accuracy = (TP + TN) / (TP + TN + FP + FN).

How well the model is able to distinguish positive events from all the cases that are expected to be positive serves as a gauge for its precision. It is calculated in this way:

TP divided by (TP + FP) is precision.

Sensitivity is also known as recall, and recall measures how well the model can distinguish positive cases from all actual positive instances. It is calculated with:

Recall is equal to TP / (TP + FN).

The F1-score provides a reasonable evaluation of the model's efficacy and is derived from mean of precision and recall. When recall and precision are optimized, it operates at its best.

2 * (Recall * Precision) / (Recall + Precision) is the F1 Score.

When combined, these evaluation parameters review in identifying human behaviors using deep learning techniques.

Table 1 Performance Metrics

Re call		F1 Score	
Accuracy	Precision		
96.84	97.47	96.38	96.74

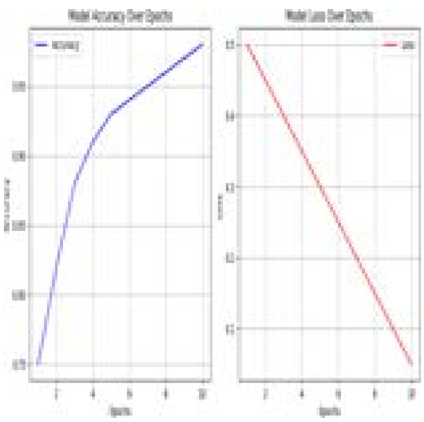

Figure 2 Accuracy Loss Graph

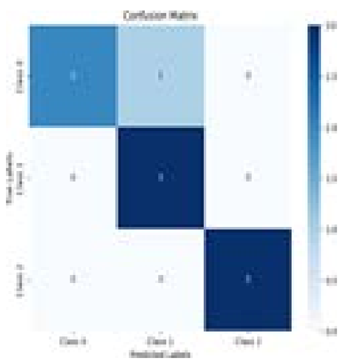

Figure 3 Confusion Matrix

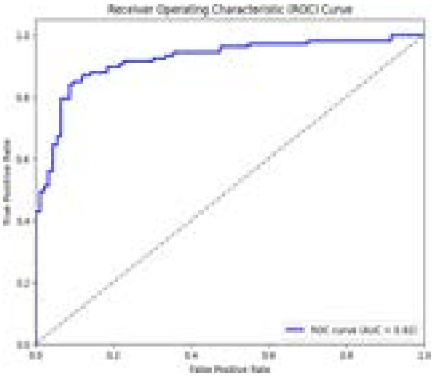

Figure 4 ROC Curve

Conclusions

In conclusion, the system demonstrates promise for identifying classifying various utilization of algorithms has proven effective in achieving high levels of accuracy in activity recognition tasks, showcasing the system's robustness and adaptability to diverse settings and activities. Despite its success, the ongoing crucial system's performance, scalability, and real- world applicability. Continued refinement in data collection, feature extraction, model optimization, and interpretability will be key to maximizing the system's utility and effectiveness in practical human activity recognition scenarios.

References

1. Yadav, S. K., Tiwari, K., Pandey, H. M., & Akbar, S. A. (2021). A review of multimodal human activity recognition with special emphasis on classification, applications, challenges and future directions. Knowledge-Based Systems, 223, 106970.
2. Ferrari, A., Micucci, D., Mobilio, M., & Napoletano, P. (2021). Trends in human activity recognition using smartphones. Journal of Reliable Intelligent Environments, 7(3), 189-213.
3. Xu, Y., & Qiu, T. T. (2021). Human activity recognition and embedded application based on convolutional neural network. Journal of Artificial Intelligence and Technology, 1(1), 51-60.
4. Ronald, M., Poulose, A., & Han, D. S. (2021). iSPLInception: An inception- ResNet deep learning architecture for human activity recognition. IEEE Access, 9, 68985-69001.
5. Zhang, S., Li, Y., Zhang, S., Shahabi, F., Xia, S., Deng, Y., & Alshurafa, N. (2022). Deep learning in human activity recognition with wearable sensors: A review on advances. Sensors, 22(4), 1476.
6. Chen, K., Zhang, D., Yao, L., Guo, B., Yu, Z., & Liu, Y. (2021). Deep learning for sensor-based human activity recognition: Overview, challenges, and opportunities. ACM Computing Surveys (CSUR), 54(4), 1-40.
7. Nafea, O., Abdul, W., Muhammad, G., & Alsulaiman, M. (2021). Sensor-based human activity recognition with spatio- temporal deep learning. Sensors, 21(6), 2141.
8. Gu, F., Chung, M. H., Chignell, M., Valaee, S., Zhou, B., & Liu, X. (2021). A survey on deep learning for human activity recognition. ACM Computing Surveys (CSUR), 54(8), 1-34.
9. Mekruksavanich, S., & Jitpattanakul, A. (2021). Biometric user identification based on human activity recognition using wearable sensors: An experiment using deep learning models. Electronics, 10(3), 308.

10. Ramanujam, E., Perumal, T., & Padmavathi, S. (2021). Human activity recognition with smartphone and wearable sensors using deep learning techniques: A review. IEEE Sensors Journal, 21(12), 13029-13040.
11. Dua, N., Singh, S. N., & Semwal, V. B. (2021). Multi-input CNN-GRU based human activity recognition using wearable sensors. Computing, 103, 1461-1478.