A SURVEY ON ANTICIPATING ACTIVITIES IN SMART HOME ENVIRONMENT

## CH. Vijaya Kumar1, Gadde Nikhitha2, Jujjuri Poojitha3, Annareddy Shreya Sree4, Soogoor Sai Praneetha5

1Assisstant Professor, Computer Science and Engineering, ACE Engineering College, India

2,3,4,5Student, Computer Science and Engineering, ACE Engineering College, India

# ABSTRACT

Human Activity Recognition (HAR) is one of the essential building blocks of so many applications like security monitoring the internet of things and human-robot interaction. The research community has developed various methodologies to detect human activity based on various input types. However, most of the research in the field has been focused on applications other than human-in-the-centre applications. Human activity recognition (HAR) based on multimodal sensors has become a rapidly growing branch of biometric recognition and artificial intelligence. However, how to fully mine multimodal time series data and effectively learn accurate behavioural features has always been a hot topic in this field. Practical applications also require a well-generalized framework that can quickly process a variety of raw sensor data and learn better feature representations. This paper focused on optimizing the input signals to maximize the HAR performance from wearable sensors. A model based on Invariant Learning Network has been proposed and trained on different signal combinations of three Inertial Measurement Units that exhibit the movement. The proposed Invariant Learning Network optimizes input signals from three Inertial Measurement Units to enhance HAR performance from wearable sensors

# INTRODUCTION

Human Activity Recognition (HAR) is a burgeoning field within mobile wearable and pervasive computing, vital for automating the detection and classification of human activities based on sensor data. HAR has gained prominence due to its multifaceted applications across various domains, including health monitoring, behavior analysis, skill assessment, and sports coaching. Its ability to interpret human actions from sensor inputs has led to the development of innovative solutions that enhance user experiences and improve quality of life.

**Significance of HAR in Various Domain**s: In health monitoring, HAR serves as a powerful tool for tracking daily activities, enabling early detection of health anomalies, and providing insights into individuals' physical well-being. Behavior analysis benefits from HAR by deciphering patterns and trends in human behavior, facilitating personalized interventions and behavior modification strategies. Similarly, HAR aids in skill assessment and sports coaching by offering real-time feedback and performance evaluation, thereby enhancing training regimens and athletic performance..

**Challenges in Traditional HAR Approaches:** Traditional HAR approaches often grapple with the complexities of feature engineering and the limitations of conventional machine learning algorithms. Designing effective features tailored to different activities can be time-consuming and may not generalize well across diverse tasks and environments. Moreover, the reliance on handcrafted features poses challenges in capturing nuanced aspects of human activities, hindering the overall performance and scalability of HAR systems.

**Rise of Deep Learning in HAR:** The advent of Deep Learning (DL) techniques has revolutionized HAR by enabling automatic feature learning from raw sensor data. DL models, such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have demonstrated remarkable capabilities in extracting high-level representations, thereby reducing the need for manual feature engineering. This paradigm shift has led to significant improvements in HAR accuracy, robustness, and scalability across various applications.

**Applications of Sensor-based HAR:** Wearable sensors, including accelerometers, gyroscopes, and magnetometers, have proliferated the applications of HAR in diverse domains. These sensors, integrated into smartphones, smartwatches, and other wearable devices, provide rich streams of data for activity recognition tasks. In health management, sensor based HAR facilitates continuous monitoring of physical activities, aiding in the diagnosis and management of chronic diseases such as cardiovascular conditions and diabetes. Similarly, in behavior analysis, sensor-based HAR enables real-time tracking of daily routines, helping individuals make informed decisions about their lifestyle choices and habits.

**Imbalanced Datasets in HAR:** Imbalanced datasets present a significant challenge in HAR, where certain activity classes may be overrepresented or underrepresented. This imbalance can lead to biased models that favor dominant classes, compromising the accuracy and generalizability of HAR systems. Addressing class imbalances requires careful data collection strategies, augmentation techniques, and algorithmic approaches such as resampling and cost-sensitive learning. By mitigating class

imbalances, researchers can develop more robust and reliable HAR models that perform well across diverse activity classes and user populations.

**User Variability in HAR:** Variability in how individuals perform activities due to personal characteristics and behaviors poses a significant challenge for HAR. Factors such as age, gender, fitness level, and cultural differences can influence the way activities are executed, leading to variations in sensor data patterns. Addressing user variability is crucial for developing HAR models that generalize well across diverse user populations. Techniques such as personalized modeling, transfer learning, and domain adaptation can help account for individual differences and improve the robustness and adaptability of HAR systems.

**Data Quality Issues in HAR Datasets:** The quality of HAR datasets directly impacts the performance and reliability of HAR models. Common data quality issues include noise, missing data, sensor drift, and labeling errors. Noise and sensor errors can introduce artifacts into the data, affecting the accuracy of activity recognition. Missing data and sensor drift can lead to inconsistencies in the dataset, making it challenging to train robust models.

**Interpretability of HAR Models:** Understanding the decisions made by HAR models is essential for trust and transparency. Interpretable models and post-hoc analysis techniques help in understanding the features driving classification decisions.

**Scalability of HAR Systems:** Scalability is crucial for real-world HAR systems as sensor data volume rises. Efficient algorithms, scalable infrastructure, and distributed computing ease computational burdens, ensuring real-time processing. Optimized data storage solutions manage large datasets, while scalable architectures enable integration across diverse environments like smart homes and healthcare facilities.

**Privacy and Ethical Considerations in HAR:** Privacy and ethical concerns arise from the collection and analysis of sensor data for HAR. Ensuring data privacy, obtaining consent, and adhering to ethical guidelines are essential for responsible HAR deployment.

# LITERATURE SURVEY

As part of the Literature Survey, we have referred few project papers and the findings from them are: As part of the Literature Survey, we have referred few project papers and findings from them are:

Ultra-Wideband Radar-Based Activity Recognition Using Deep Learning: Farzan M. Noori, Md. Zia Uddin and Jim Torresen

(2021) [1]

In this study, a novel approach was proposed for HAR using a UWB sensor and state-of-theart deep learning models. This paper presents a novel sensing approach based on deep learning for human activity recognition using a nonwearable ultrawideband (UWB) radar sensor. UWB sensors protect privacy better than RGB cameras because they do not collect visual data. (LSTM). Conventional training approaches were also tested to validate the superiority of LSTM.

Human Activity Recognition Based on Improved Bayesian Convolution Network to Analyze Health Care Data Using Wearable IoT Device: Zhiqing Zhou , Heng Yu and Hesheng Shi (2020) [2]

Within this report, a revolutionary IoT framework is introduced for the long-term, individual monitoring of a person’s activities. Improved Bayesian Convolution Network (IBCN) is proposed by wearable sensors of different kinds of uncertainty for human activity. The device includes a wearable sensor and Deep Learning technology to provide information about a variety of behaviors aimed at deducting suspicious activity.

LSTM-CNN Architecture for Human Activity Recognition: Kun Xia, Jianguang Huang and Hanyu Wang (2020)[3]

A novel deep neural network that combines convolutional layers with LSTM for human activity recognition was pro- posed in this paper. The weight parameters of CNN mainly concentrate on the fully-connected layer, which greatly reduces the model parameters while maintaining a high recognition rate. Moreover, a BN layer is added after the GAP layer to speed up the convergence of the model and obvious effect was obtained.

Design and Implementation of a Convolutional Neural Network on an Edge Computing Smartphone for Human Activity Recognition: Tahmina Zebin , Patricia J. Scully , Niels Peek, Alexander J. Casson and Krikor B. Ozanyan (2019) [4]

A deep convolutional neural network model for the classification of daily-life activities using raw accelerometer and gyroscope data of a wearable sensor as the input. Our experimental results demonstrate how these characteristics can be efficiently extracted by automated feature engine in CNNs.

Developing a Lightweight Rock-PaperScissors Framework for Human Robot Collaborative Gaming: Heike Brock, Javier Ponce Chulani, Luis Merino , Deborah Szapiro and Randy Gomez (2020)[5]

In this paper, we presented a novel framework for a social and entertaining RPS play interaction between a robot and a human player. The first architecture is used to recognize and segment human motion activity in order to initialize the RPS play, and the second architecture is used to classify hand gestures into rock, paper or scissors. As such, it offers a powerful application for the subsequent exploration of social humanmachine interaction.

Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning: Ran Zhu, Zhuoling Xiao, Ying Li , Mingkun Yang, Yawen Tan , Liang Zhou , Shuisheng Lin and Hongkai Wen (2019)[6]

This paper has proposed a CNN-based human activity recognition model using the nine-axis motion signals of accelerometer, gyroscope and magnetometer in common smartphones. We have compared and analyzed the performance of different algorithms with seven daily activities and four different placements of smartphones.The CNN-Based model demonstrates robust performance in recognizing daily activities across various smartphone placements, leveraging nine-axis motion signals from accelerometer, gyroscope, and magnetometer sensors.

Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning: Ran Zhu, Zhuoling Xiao, Ying Li , Mingkun Yang, Yawen Tan , Liang Zhou , Shuisheng Lin and Hongkai Wen (2019)[7]

This paper has proposed a CNN-based human activity recognition model using the nine-axis motion signals of accelerometer, gyroscope and magnetometer in common smartphones. We have compared and analyzed the performance of different algorithms with seven daily activities and four different placements of smartphones.The CNN-Based model demonstrates robust performance in recognizing daily activities across various smartphone placements, leveraging nine-axis motion signals from accelerometer, gyroscope, and magnetometer sensors.

An Efficient Activity Recognition Framework: Toward Privacy-Sensitive Health Data Sensing- 2017 [8]

In this paper, the authors propose a framework for efficiently recognizing human activities in smart homes using spatiotemporal mining techniques. Additionally, they introduce a modified micro-aggregation approach to enhance the privacy of collected human activity data. The framework demonstrates promising results in terms of accuracy and privacy-utility tradeoff through extensive validation on benchmark datasets. The approach leverages weighted profiling for improved accuracy and incorporates a privacy-preserving technique based on modified k-anonymity. Future research may explore extending these techniques to handle distributed sensor data and evaluate their resilience against inference attacks.

Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition-2017[9]

The study explores utilizing smartphones' embedded sensors for efficient human activity recognition. Data sequences are collected during various daily activities, segmented using a cycle detection algorithm, and characterized by time, frequency, and wavelet domain features. Personalized and generalized models using diverse classification algorithms are developed and evaluated using 27,681 sensory samples from 10 subjects. Results indicate high accuracy, with F-scores of 95.95% and 96.26% for personalized and generalized models, respectively. Challenges include smartphone positioning variability and sensor accuracy. The proposed framework employs detailed feature extraction and statistical analysis for precise activity pattern characterization, demonstrating effectiveness for practical implementation.

iSPLInception: An Inception-ResNet Deep Learning Architecture for Human Activity Recognition -2021[10]

This paper introduces iSPLInception, a deep learning model designed for human activity recognition (HAR) that aims to achieve high predictive accuracy while using fewer computational resources. Based on the Inception-ResNet architecture, iSPLInception outperforms existing DL models on four public HAR datasets from the UCI machine learning repository in terms of accuracy, cross-entropy loss, and F1 score. The proposed model is evaluated on various datasets, including those from smartphones and physical activity monitoring, demonstrating remarkable performance in HAR applications. Comparison with previous works highlights iSPLInception's superiority across all benchmarked datasets, despite challenges posed by dataset imbalances.

# COMPARISION ANALYSIS

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **S.No** | **Paper Title** | **Work done on paper** | **Future work** | **Drawbacks** |
| 1. | FarzanM. Noori, Md. Zia Uddin Jim Torresen; Ultra Wideband Radar-Based Activity Recognition Using Deep Learning; 2021 | This paper presents a novel sensing approach basedon deep learning for human activity recognition using a non-wearable ultra-wideband (UWB) radar sensor.UWB sensors protect privacy. | The proposed method can be Applied in many prominent fields,including human robot interaction for various practical applications Such as mobile robotsfor eldercare. | -Maximizes complexity of theproblem-It is not an easy-to-use method-Have not been investigated thoroughly |
| 2. | Zhiqing Zhou , Heng Yuand HeshengShi; Human ActivityRecognition Based on Improved Bayesian Convolution Network to Analyze Health CareData Using Wearable IoT Device; 2020 | Within this report, a revolutionary IoT framework is introduced for the long- term,individual monitoring of a personsactivities. | Furthermore, lab-scale experimental analysis on patients health data classification accuracy hasbeen considerably developed. | -Significantly increases capital andoperating expenditures-High complexity, inaccuracy, and inadequacy-Difficulties toobtain better performance |
| 3. | Kun Xia, Jianguan g Huangand Hanyu Wang;LSTM-CNNArchitecture for Human Activity Recognition; 2020 | A deep neural network that combines convolutionallayers with LSTM for HAR was pro- posed in thispaper. | It can’t adaptively extra captivityfeatures and has fewer parameters with lessaccuracy. | -Difficult to be used inlarge scale parallel computing.-High complexity of installing and maintaining-Cannot meet current network business demands |
| 4. | TahminaZebin, Patricia J.Scully,Niels Peek,Alexand er J. Cassonand Krikor B. Ozanyan; Design and Implementationof a CNN onan Edge Computing SmartphoneforHAR, 2019 | A deep convolutional neural Network model for the Classification ofdaily-life activities using raw accelerometer and gyroscope data of a wearable sensor as the input. | This paper suggests feature characteristics can be efficientlyextracted by automated feature engine in CNNs. | -Significantly increases capital andoperating expenditures-Difficult to be used in large- scale parallel computing. |
| 5. | Heike Brock,Javier Ponce Chulani,Luis Merino , Deborah Szapiro and Randy Gomez; Developing aLightweight Rock- Paper- Scissors Framework for HumanRobot CollaborativeGaming; 2020 | In this paper, we presented a novel framework for asocialand entertaining RPSplay interaction between arobotanda human player. | The overall design is computationally lightweightand ubiquitous andonly relies on asingle LeapMotion controller. | * Heavyweight
* Approach is abittime- consuming

This system is Opportunistic and uncontrollable |

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| 6. | Ran Zhu,Zhuoling Xiao, Ying Li , Mingkun Yang, Yawen Tan; Efficient Human Activity Recognition Solvingthe Confusing Activities ViaDeep Ensemble Learning;2019 | This paper has proposed a CNN- basedHAR model using the nine-axis motion signals of accelerometer in smartphones. | The performancee of different algorithms with seven daily activities can be better with other algorithms. | -Difficulties toobtain better performance-Unsuitable forlarge scale scenarios. |
| 7. | Daniele Rav, Charence Wong, BennyLo and Guang- ZhongYang; A Deep Learning Approach to on-Node Sensor Data Analytics forMobile or WearableDevices; 2017 | The proposed method is designed to overcomesome of the issues typically presenting adeep learning framework whenon-node computation is required. | The accuracy ofthe proposed method can be improved when compared to the Current state approaches. | -Difficult to be used inlarge scale parallel computing.-It is not an easy- to-use method Solutions have been proved ineffective |
| 8 | Mutegeki Ronald,Alwin Pouloseand Dong Seog Han; iSPLInception: An Inception- ResNet Deep Learning Architecture forHuman Activity Recognition; 2021 | -Proposed iSPL Inception modelfor HAR.-Inspired by Inception- ResNet architecture.Evaluated on fourHAR datasets. | Future work could focus onoptimizing robustness and scalability. | Difficult and Less Commonly usedHave not been investigated thoroughly Cannot meet current network businessdemands |

1. **FUTURE SCOPE**

In the future, this CNN-based human activity recognition model could undergo refinement to enhance its accuracy and efficiency across various smartphone placements and activity types. Transferlearning techniques could be explored to adapt the model to diverse environments and user populations, while integrating additional sensor modalities could enrich its input data and broaden its application scope.

Real-time implementation frameworks couldenable continuous activity monitoring on resource-constrained devices, facilitating feedbackmechanisms in everyday scenarios. Furtherresearch could focus on federated learning approaches for collaborative model training while preserving data privacy. Context-awareness techniques could improve the model's adaptability to changing environmental conditions and user contexts, enhancing its robustness in real-worldsettings.

Expanding the model's capabilities to recognizespecialized activities relevant to healthcare, sports,or industrial contexts could unlock new applications and use cases. Collaboration with experts in related fields could enrich the model's understanding of human behavior and improve its interpretability. Benchmarking against state-of-the- art approaches and establishing standardized evaluation metrics could facilitate fair comparison and drive advancements in the field. Integration with emerging technologies like augmented reality or edge computing could enable innovative applications in immersive simulations, personalized coaching, and interactive environments. Overall, the future of this project holds promise for advancing human activity recognition technology and its practical applications across various domains.

# CONCLUSION

In conclusion, the utilization of energy harvesting edge devices for increasingly complex tasks like Human Activity Recognition (HAR) necessitates targeted efficiency-maximizing optimizations in both system and node designs. This paper proposes a novel approach using a Generative Adversarial Network (GAN) framework to generate human activity sensor data, which is then employed to balance existing datasets. By incorporating an autoencoder to provide prior knowledge for all activity classes and introducing conditional constraints for generating activity data for specific classes, the framework enhances the stability of the training process. Experiments conducted on two public human activity datasets demonstrate a significant improvement in HAR classifier performance after dataset balancing. This research highlights the potential of advanced machine learning techniques to address challenges in HAR and offers valuable insights for optimizing edge device performance in energy-constrained environments.

# REFERENCES

[1]. Ultra-Wideband Radar-Based ActivityRecognition Using deep Learning:Farzan M. Noori , Md. Zia Uddin and JimTorresen(2021) [https://ieeexplore.ieee.org/document/9558753](https://ieeexplore.ieee.org/document/95%2058753)

[2]. Human Activity Recognition Based on Improved Bayesian Convolution Network to Analyze Health Care Data Using Wearable IoT Device: ZhiqingZhou , Heng Yu and Hesheng Shi (2020)[https://ieeexplore.ieee.org/document/90](https://ieeexplore.ieee.org/document/90%2086799) [86799](https://ieeexplore.ieee.org/document/90%2086799)

[3]. LSTM-CNN Architecture for Human Activity Recognition: Kun Xia ,Jianguang Huang and Hanyu Wang (2020) [https://ieeexplore.ieee.org/document/9043535](https://ieeexplore.ieee.org/document/90%2043535)

[4]. Design and Implementation of a Convolutional Neural Network on anEdge Computing Smartphone for Human Activity Recognition: Tahmina Zebin

[5]. Developing a Lightweight Rock-Paper- Scissors Framework for Human Robot Collaborative Gaming: Heike Brock , Javier Ponce Chulani , Luis Merino , Deborah Szapiro and Randy Gomez (2020)

[6]. Efficient Human Activity Recognition Solving the Confusing Activities Via Deep Ensemble Learning: Ran Zhu , Zhuoling Xiao , Ying Li , Mingkun Yang, Yawen Tan , Liang Zhou , Shuisheng Lin and Hongkai Wen (2019)

[7]. A Deep Learning Approach to on-Node Sensor Data Analytics for Mobile or Wearable Devices: Daniele Rav , CharenceWong , Benny Lo and GuangZhong Yang (2017)

[8]. Performance Analysis of Smartphone-Sensor Behavior for Human Activity Recognition: Yufei Chen and Chao Shen [2017]

[9]. "Real-time food intake classication andenergy expenditure estimation on a mobiledevice,D. Ravi, B. Lo, and G.-Z.

Yang

[10]. An agent-based smart home,D. J. Cook etal.,

[11]. An Efficient Activity RecognitionFramework: Toward Privacy-SensitiveHealth Data Sensing: Samer Samarah , Mohammed Gh. Al Zamil , Ahmed F. Aleroud , Majdi Rawashdeh , Mohammed F.Alhamid and Atif Alamri [2017] [12]. Accurate and privacy preserving coughsensing using a low-cost microphone,E. C. Larson, T. Lee, S. Liu,

[13]. Convolutional neural networks for human activity recognition using mobile sensors,M. Zeng, L. T. Nguyen, B.

Yu, O. J.Mengshoel, J. Zhu, P. Wu, and J. Zhang

[14]. The opportunity challenge: A benchmark database for on-body sensor-based activityrecognition, Pattern Recognition R.

Chavarriaga, H. Sagha, A. Calatroni, S. T.Digumarti, G. Trster, J. D. R. Milln, and D.Roggen

[15]. A hybrid FMCW-interferometry radar forindoor precise positioning and versatile life activity monitoring,G. Wang, C.

Gu,T. Inoue, and C. Li

[16]. Unobtrusive sensing and wearable devicesfor health, Y.-L. Zheng et al. [17]. Social cycling and conditional responses,Z.Wang, B. Xu, and H.-J. Zhou

[18]. "Detection of daily activities and sportswith wearable sensors in controlled and uncontrolled, M. Ermes, J. Prkk, J. Mntyjrvi, and I. Korhonen