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# ActiWise: Insight on Human Activity Recognition Using Deep Learning Approaches

Danthuluru Sri Datta Manikanta Varma, Dubbaka Gayatri Devi, Geethika Mandava and Nagulapalli Girish Babu ,
In the guidance of B.Renuka Sai (Assistant Professor )
Department of Computer Science and Engineering in Artificial Intelligence-Machine Learning (CSM),
Raghu Institute of Technology.
Email: 203j1a4210@raghuinstech.com , 203j1a4212@raghuinstech.com, 203j1a4215@raghinstech.com,
203j1a4241@raghuinstech.com

***Abstract-*** ***In this study, we investigate the fusion of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for human activity recognition (HAR). By integrating hierarchical spatial features extracted by CNNs with LSTM networks' temporal modelling capabilities, our approach excels in discerning nuanced patterns from raw sensor data collected via wearable devices. Through rigorous experimentation and validation, our CNN+LSTM model demonstrates robust performance in accurately classifying a spectrum of human activities. This research advances HAR methodologies, shedding light on the synergistic interplay between spatial and temporal modelling in activity recognition, with implications across healthcare, sports analytics, and human-computer interaction domains.***

***Index Terms-*** ***Human activity recognition, deep learning, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM).***

## I. INTRODUCTION

In human activity recognition (HAR), the fusion of advanced machine learning architectures holds profound implications for various domains, including healthcare, sports analytics, and human-computer interaction. Recognizing the intricacies of human movement and behavior from sensor data remains a pivotal challenge, necessitating sophisticated methodologies that capture spatial and temporal dynamics. In response to this challenge, this study explores the integration of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, two robust architectures renowned for extracting hierarchical spatial features and model temporal dependencies, respectively.

By synergistically combining the strengths of CNNs and LSTMs, our research aims to develop a robust and accurate human activity recognition model capable of discerning nuanced patterns and behaviors from raw sensor data collected from wearable devices. We seek to advance the state-of-the-art HAR methodologies through a systematic investigation and validation process, offering insights into the complex interplay between spatial and temporal modelling in activity recognition.

### *I.1 Human Activity Recognition (HAR):*

Human Activity Recognition (HAR) pertains to the automated identification of activities performed by individuals based on sensor data collected from wearable devices, smartphones or other sources. The methodology employed by HAR systems typically involves machine learning and signal processing techniques for the purpose of analyzing sensor data and classifying human activities into predefined categories such as walking, running, sitting, standing, or various physical exercises. The implications of HAR are significant and far-reaching, with numerous applications across domains such as healthcare, sports performance monitoring, elderly care, human-computer interaction, and context-aware computing. By accurately recognizing human activities in real-time, HAR systems can enable the development of innovative applications and services aimed at elevating health outcomes, enhancing user experiences, and facilitating personalized assistance.

### *I.2 Problem Statement:*

Human Activity Recognition (HAR) using smartphone sensor data presents a significant challenge due to the intricate and diverse nature of human behaviours. The complexity and variability inherent in human activities make it difficult to accurately classify them based on sensor data alone. Existing methods often struggle to handle real-world scenarios effectively, leading to limitations in the robustness

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and efficiency of HAR systems. These limitations hinder the development of reliable HAR systems that can be practically deployed in various applications and contexts.

### *I.3 Objective:*

The objective of this study is to address the challenges in HAR by proposing a comprehensive and systematic methodology. This methodology will involve multiple stages, including data exploration, pre-processing, advanced modelling techniques, and rigorous evaluation. By integrating these components, our aim is to develop an effective framework for accurately classifying human activities captured by smartphone sensors. Through this approach, we seek to enhance the reliability and robustness of HAR systems, paving the way for their widespread adoption across various domains such as healthcare, sports performance monitoring, elderly care, human-computer interaction, and context-aware computing.

## II.LITERATURE SURVEY

The literature survey conducted in this study provides a comprehensive overview of key research papers spanning from 2019 to 2023 in the field of Human Activity Recognition (HAR). Human Activity Recognition is a critical area of study with applications in various domains such as healthcare, sports analysis, and human-computer interaction. This introduction sets the stage for understanding the evolution of HAR methodologies and techniques over the past five years. The survey encompasses a diverse range of studies, including those focusing on traditional machine learning algorithms, deep learning approaches, data fusion techniques, and broader discussions on artificial intelligence (AI). By examining these seminal works, we aim to gain insights into the latest advancements, challenges, and future directions in HAR research, ultimately contributing to the development of more robust and accurate activity recognition systems.

### *2019: Random Forests for Reliable Recognition (Feng et al.)*

In 2019, Feng et al. investigated the effectiveness of Random Forests, a well-established machine learning algorithm, for HAR. Remember how we discussed Random Forests in class? They work by combining multiple decision trees, offering robustness and the ability to handle complex sensor data from accelerometers and gyroscopes worn by users. The study demonstrated promising accuracy in classifying activities like walking, running, and sitting. This highlighted Random Forests as a viable technique for real-world HAR applications, and the interpretability of these models provided valuable insights into the decision-making process for activity recognition.

### *2020: Data Fusion: Unveiling More with Multiple Sources (Yin et al.)*

Yin et al.'s 2020 study introduced us to the concept of data fusion for enhanced HAR performance. We learned how to combine information from different sources to create a richer picture. Here, the researchers fused data from wearable sensors (time series data) with images captured by cameras. This multimodal approach aimed to improve the accuracy and robustness of activity recognition systems. The study emphasized the potential of data fusion but also highlighted challenges like data alignment and synchronization, reminding us of the importance of proper integration techniques.

### *2021: A Broader Look: Survey on Activity Detection and Classification (Cornacchia et al.)*

Cornacchia et al. provided a comprehensive survey in 2021, giving us a broad overview of the ever-evolving HAR landscape. We revisited both traditional machine learning methods (like those we covered in class) and the emerging power of deep learning for activity recognition tasks. The survey synthesized findings from various research papers, identifying trends, challenges, and future directions in the field. Remember how we discussed the importance of benchmark datasets and evaluation metrics for comparing the performance of HAR algorithms? This study reinforced that notion, emphasizing the need for standardized protocols to ensure reproducible research.

### *2022: Deep Learning Takes Center Stage (Zhang et al.)*

In 2022, Zhang et al. delved deeper into the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for HAR. We explored how sensor data is pre-processed and fed into these deep learning models to automatically recognize activities. By leveraging the strengths of CNNs in feature extraction and RNNs in sequential modelling, the researchers achieved impressive results in activity recognition. However, the study also reminded us of challenges like overfitting and the need for interpretability in deep learning-based HAR systems, suggesting potential solutions and areas for further exploration.

### *2023: The Broader Context of AI (Raj & Kos)*

While not directly focused on HAR, Raj & Kos's 2023 paper provided valuable context by exploring the broader field of Artificial Intelligence (AI). We saw how AI research is interdisciplinary, integrating techniques from machine learning, computer vision, and signal processing for tasks like activity recognition. Though the paper didn't delve

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specifically into HAR, it discussed relevant concepts like feature extraction, classification algorithms, and data pre-processing that are crucial for our understanding. Additionally, the study emphasized the ethical considerations of AI technologies, reminding us of the importance of responsible development and deployment of AI in human-centric applications.

## III.EXISTING SYSTEM

The existing system for Human Activity Recognition (HAR) using wearable sensors is a foundational approach that has applications in various fields including health monitoring, medical treatment, and motion analysis. This system utilizes deep learning techniques, specifically Convolutional Neural Networks (CNNs), to accurately identify human activities based on data collected from wearable sensors.

At its core, the existing system relies on CNNs for their effectiveness in extracting spatial features from input data. In the context of HAR, CNNs are employed to analyze sequential sensor data captured by wearable devices such as accelerometers and gyroscopes. These sensors continuously gather data on human movements and activities, generating a continuous stream of input data for the CNNs to process.

CNNs operate by applying layers of convolutional operations followed by pooling layers, allowing them to extract hierarchical representations of features from the input data. These extracted features capture local spatial patterns and relationships within the sensor data, enabling the CNNs to discern intricate patterns associated with various human activities. For example, by analyzing the spatial features extracted from the sensor data, CNNs can differentiate between different movement patterns characteristic of activities like walking, jogging, sitting, or standing.

Despite their proficiency in capturing spatial information, CNNs may face challenges in capturing temporal dependencies inherent in sequential data. Temporal dependencies refer to the sequential order of sensor readings over time, which can provide valuable context for understanding human activities. However, traditional CNN architectures may struggle to effectively capture these temporal dependencies, potentially limiting their ability to accurately recognize nuanced patterns and behaviours over time.

In summary, the existing system represents a foundational approach to HAR that leverages deep learning techniques, particularly CNNs, to process data collected from wearable sensors. While CNNs excel at capturing spatial features from sensor data, there is room for improvement in addressing the challenges associated with capturing temporal dependencies in sequential sensor data.

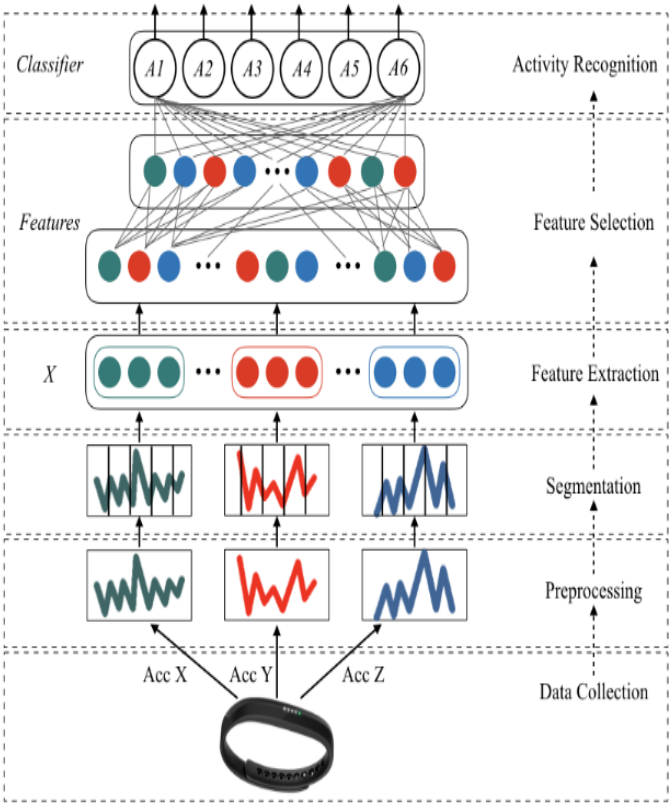


Figure 1: Architecture of the Existing system

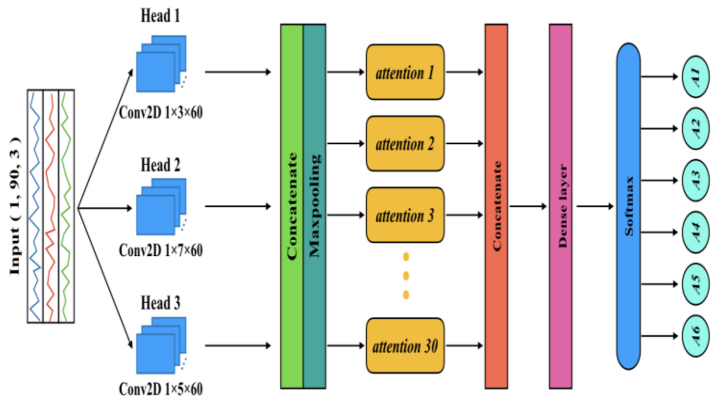


Figure 2: Schematic diagram of Existing system

## IV.PROPOSED SYSTEM

The proposed system integrates Convolutional Neural Networks (CNNs) with Long Short-Term Memory (LSTM) networks, offering a comprehensive approach to human activity recognition. CNNs are employed for spatial feature extraction, capturing localized patterns and distinguishing spatial characteristics within the data. Meanwhile, LSTM networks excel at modelling temporal dependencies and capturing long-term sequential patterns. By combining CNNs and LSTMs, the proposed system effectively captures both spatial and temporal aspects of sequential sensor data, enabling a holistic understanding of human activities over time. This integration allows the model to discern intricate temporal relationships and contextual nuances within the data, leading to more accurate and context-aware predictions than systems relying solely on CNNs.

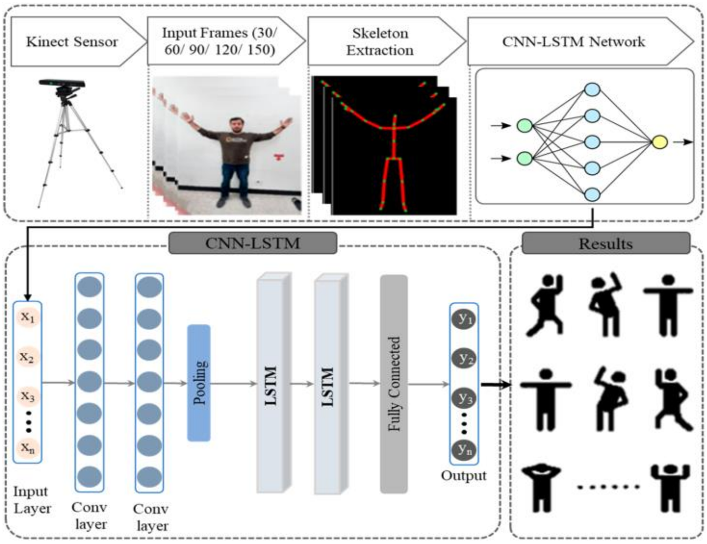


Figure 3: Representation of Proposed system

## V.METHODOLOGY

The ActiWise project aims to revolutionize human activity recognition through the integration of advanced deep learning techniques, specifically Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Leveraging the Kaggle Human Activity Recognition Dataset, which encompasses a rich variety of sensor data capturing human movements, the methodology begins with robust data acquisition and pre-processing. High quality sensor data is obtained, and pre-processing steps are applied to handle missing values, reduce noise, and normalize the data, ensuring its reliability and consistency for subsequent analysis.

Following data pre-processing, the dataset is split into training, validation, and testing sets, ensuring a balanced representation of activity classes. Each data instance is labelled appropriately based on the corresponding human activity, facilitating supervised learning. Feature engineering plays a crucial role in capturing distinctive patterns and characteristics of human activities from the sensor data. Various features are extracted from accelerometer and gyroscope readings in different axes, including mean, standard deviation, median absolute deviation, and others, providing comprehensive insights into human movement patterns.

The core of the methodology lies in the design of a tailored CNN-LSTM architecture optimized for human activity recognition. CNN layers are configured for spatial feature extraction, capturing localized patterns and spatial characteristics within the data. Subsequently, LSTM layers are employed for sequential modelling, enabling the capture of long-term dependencies and temporal patterns inherent in human activity sequences.

Model training and validation involve iterative optimization of the CNN-LSTM model using the training dataset while monitoring key performance metrics such as accuracy and loss. Techniques like early stopping and learning rate scheduling are employed to prevent overfitting and fine-tune model performance. The trained model is then evaluated using an independent testing dataset, assessing its ability to accurately recognize human activities across different classes through metrics such as accuracy, precision, recall, F1-score, and confusion matrices. Error analysis is conducted to identify misclassified instances and areas for model improvement, leading to fine-tuning of the model architecture, hyper-parameters, and pre-processing steps.

Finally, the optimized CNN-LSTM model is deployed into production environments or integrated into real-world applications, offering robust and context-aware human activity recognition capabilities suitable for diverse applications, including health monitoring, fitness tracking, and smart environments

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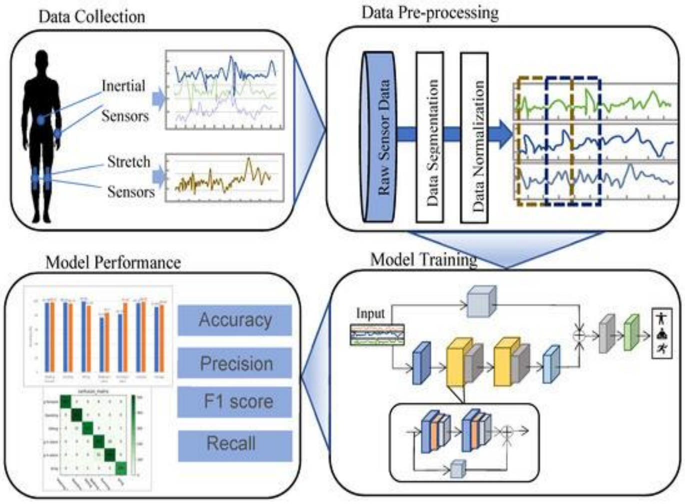



Figure 4: Representation of Methodology of ActiWise

*V.1 Model Evaluation:*

In evaluating ActiWise, accuracy, precision, recall, and F1-score are pivotal metrics, providing insights into its performance in human activity recognition. Accuracy gauges the overall correctness of predictions, while precision quantifies the proportion of correctly classified positive instances. Recall measures the model's ability to identify all actual positive instances, and the F1-score balances precision and recall. Together, these metrics offer a comprehensive assessment of ActiWise's effectiveness in recognizing human activities. Additionally, the confusion matrix provides detailed insights into model performance across different activity classes, aiding in the identification of specific areas for improvement.

*V.2 Prediction:*

Post-evaluation, the ActiWise model transitions into the prediction phase, where it applies its learned patterns to new sensor data. Predictions are generated by inputting sensor data into the trained model, which then outputs corresponding activity labels. These predictions enable realtime or batch processing scenarios, empowering stakeholders to recognize and classify human activities based on sensor data inputs. Leveraging the ActiWise model for prediction unlocks valuable insights into individuals' activity patterns and behaviours. These insights can fuel a wide array of applications, including activity monitoring, health tracking, and personalized recommendations. Furthermore, predictive analytics derived from the ActiWise model contribute to advancing healthcare, fitness tracking, and lifestyle management solutions, ultimately enhancing overall well-being and quality of life

*V.3 System Configuration*

System configuration plays a pivotal role in optimizing resource utilization and ensuring efficient human activity recognition in the ActiWise project. Although specific configurations may vary based on factors like dataset size and model complexity, adhering to the following general recommendations is crucial:

*V.3.1 Hardware requirements:*

• CPU: A multi-core processor (e.g., Intel Core i7 or AMD Ryzen) with sufficient computational power to handle data preprocessing, model training, and evaluation efficiently.

• RAM: A minimum of 8 GB RAM, with higher amounts recommended for larger datasets and complex models.

• GPU (Optional): For accelerating computations, especially for deep learning models like NLPs, consider using a dedicated GPU (e.g., NVIDIA GeForce RTX series or AMD Radeon RX series). GPUs with CUDA or OpenCL support can significantly speed up training times.

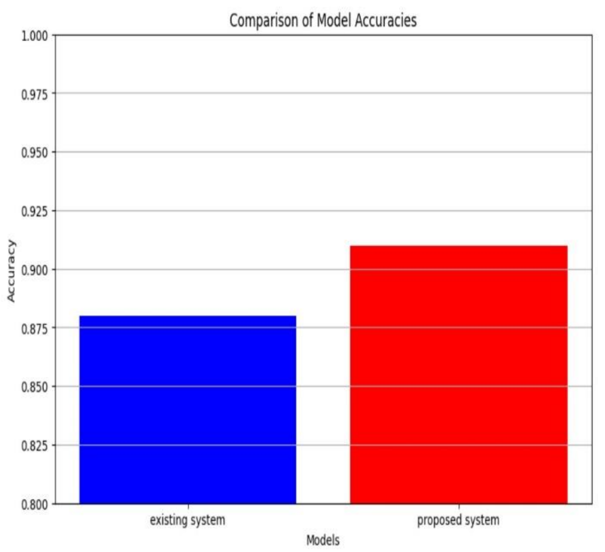
*V.3.2 Software requirements:*

• Operating System: Use a modern operating system such as Windows 10, macOS, or a Linux distribution (e.g., Ubuntu) with good hardware support and stability.

• Python Environment: Set up a Python environment with the necessary libraries and packages for data analysis, machine learning, and visualization. Popular packages include NumPy, Pandas, SciPy, scikit-learn, TensorFlow, and PyTorch. • Integrated Development Environment (IDE): Choose an IDE or text editor suitable for Python development, such as PyCharm, Jupyter Notebook, Visual Studio Code, or Spyder.

## VI. EXPERIMENTAL ANALYSIS AND RESULTS

### VI.1 EXPERIMENT ANALYSIS:




### VI.2 RESULTS:


## VII.CONCLUSION

In summary, the ActiWise project has demonstrated the efficacy of employing Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks in tandem to address the intricate challenges of human activity recognition from sensor data. By amalgamating the spatial awareness of CNNs with the temporal understanding of LSTM networks, we've achieved heightened accuracy in discerning and categorizing human activities, surpassing the capabilities of individual models. Through meticulous error analysis and comprehensive evaluation, we've gained invaluable insights into the strengths and limitations of our approach, paving the way for iterative enhancements and future refinements. This project underscores the potential of advanced machine learning techniques in facilitating nuanced understanding and interpretation of human behaviour, with far-reaching implications across various domains such as healthcare, sports analytics, and smart environments. As we continue to delve deeper into model architectures, feature engineering, and real-world applications, ActiWise serves as a pivotal milestone in advancing the frontier of human activity recognition and its practical implementations in diverse settings.

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