Complex Human Activities Recognition Using Smartphone Sensors: A Deep Learning Approach

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Citation | Saeed. M, Awan. A, Hameed. S "Complex Human Activities Recognition Using Smartphone Sensors: A Deep Learning Approach", IJIST, Special Issue. pp 172-184, Oct 2024
Received| Oct 09, 2024 **Revised|** Oct 15, 2024 **Accepted|** Oct 20, 2024 **Published|** Oct 25, 2024.

Human Activity Recognition (HAR) plays a critical role in understanding human behavior, with mobile phone sensors offering a promising approach for practical applications. This research uniquely addresses the challenge of Complex Human Activity Recognition (CHAR) using Long Short-Term Memory (LSTM) networks, advancing beyond basic activity recognition. LSTM was applied to three publicly available datasets—PAMAP2, Complex Human Activities, and WISDM—using accelerometer, gyroscope, and magnetometer sensor data. The research evaluated the effectiveness of both single-sensor (accelerometer) and multi-sensor combinations for recognizing complex activities. The study achieved 94-98% accuracy across datasets, showing that a single accelerometer sensor provides reasonable accuracy, while adding more sensors, like gyroscope and magnetometer, further boosts performance at a resource cost. The LSTM-based approach consistently outperformed traditional methods, including CNNs, in complex activity recognition, demonstrating its robustness in simplifying sensor requirements without compromising accuracy. LSTM networks offer an efficient and accurate solution for complex human activity recognition, balancing performance and resource optimization.

Introduction:

Considerable progress has been made in the field of Artificial Neural Networks (ANN) in terms of computational performance and accuracy [59]. Deep learning methods such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) are particularly effective in extracting features from various data types, playing vital roles in domains like Natural Language Processing (NLP) and Computer Vision (CV) [1].

Deep learning gained widespread attention with the success of the AlphaGo program, which defeated top-ranking Go player Lee Sedol. Google's substantial investments in deep learning, including projects like AlphaGo, voice recognition systems, and self-driving cars, underscore the technology's potential [7,10]. For instance, deep learning systems are used for selecting attractive thumbnails from YouTube videos and for automated email responses via Google Reply. Human Activity Recognition (HAR) is another promising application, where different patterns of activity are classified based on sensor-collected time series data, such as those from gyroscopes and accelerometers [13]. Therefore, deep learning approaches can significantly contribute to the HAR area of research also [3].

Conventional approaches struggle with recognizing complex human activities due to their reliance on static, handcrafted feature extraction [5]. Recognizing complex activities is challenging, as these actions often involve combinations of simpler activities, making them harder to identify with traditional methods. Figure 1 shows the flow diagram of the activity recognition process, highlighting the stages involved in addressing these complexities. Multiple sensors are typically employed to achieve high accuracy in complex activity recognition, but this study focuses on leveraging deep learning for this purpose. Researchers have made notable strides in HAR using both vision-based and sensor-based approaches. Vision-based HAR utilizes images captured by cameras to identify human behavior, with studies showing successful gesture recognition using depth cameras and multi-class SVMs [8]. However, privacy issues, coverage limitations, and difficulties in extracting exact postures from varied backgrounds present significant drawbacks [4]. To mitigate these issues, wearable sensor-based approaches have been developed. Mobile phones, equipped with various sensors like GPS, gyroscopes, accelerometers, magnetometers, and microphones, are increasingly used for activity recognition due to their widespread availability and battery efficiency [15, 19].

Several studies have employed machine learning techniques such as Decision Trees, Support Vector Machines (SVM), and Hidden Markov Models (HMM) for simple activity recognition [6]. Despite their effectiveness for basic activities, these traditional methods rely heavily on handcrafted features, which limit their performance in recognizing complex activities. Recent research has highlighted the potential of deep learning models, such as Deep Belief Networks (DBN), RNNs, and CNNs, to overcome these limitations by automatically learning high-level features [20,22]. This research is structured to first discuss the limitations of traditional machine learning approaches and then delve into the proposed deep learning methods. Data collection and preprocessing techniques are outlined, followed by an exploration of feature extraction and model training processes. The study then compares the performance of deep learning models with conventional methods in recognizing complex human activities.

The main objectives of this study are to recognize complex human activities using smartphone sensors and to demonstrate the superiority of deep learning approaches over traditional machine learning methods in terms of accuracy. This research contributes to the field by using Long Short-Term Memory (LSTM) networks on publicly available datasets, achieving high accuracy with single sensor data and further improvements with multiple sensors. The novelty of this work lies in its focus on complex human activity recognition using deep learning, providing solutions where traditional methods fall short.

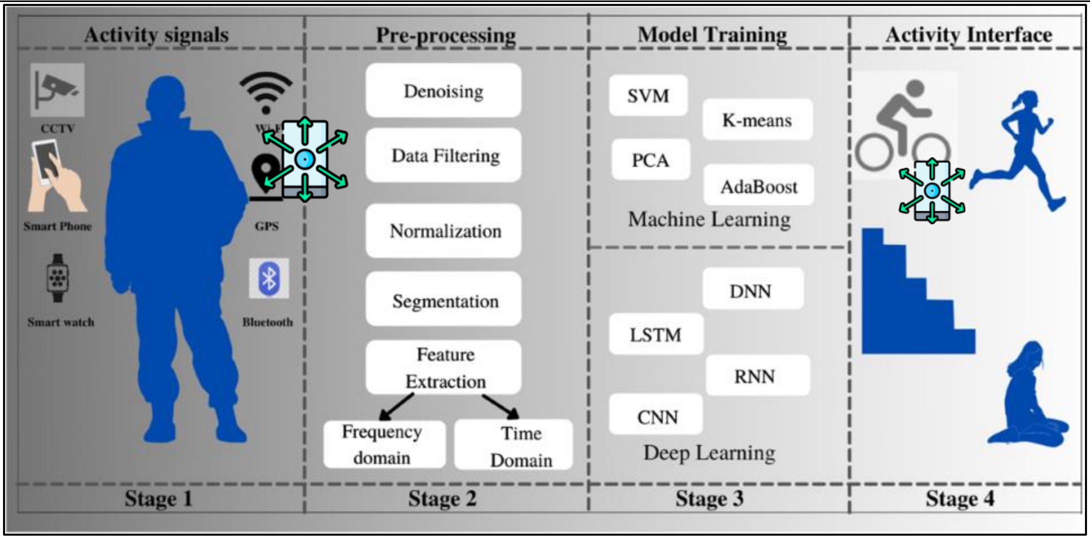

Figure 1. Flow Diagram of CHAR

Material and Methods:

Related Work:

Human Activity Recognition (HAR) has seen significant advancements in recent years, driven by studies using datasets such as those discussed in [1, 2]. These datasets, including accelerometer and gyroscope data, have primarily been collected in controlled laboratory environments, facilitating reliable analysis of activities such as walking, running, and sitting [3, 4]. For instance, [5] compared machine learning algorithms like Convolutional Neural Networks (CNN), Random Forest (RF), K-Nearest Neighbors (KNN), and Principal Component Analysis (PCA), concluding CNN as the most effective for HAR, especially with optimized architectures. Similarly, [6, 7] proposed a CNN model that improved performance over previous methods, highlighting the effectiveness of deep learning in feature extraction.

Deep learning techniques, such as Deep Belief Networks (DBN) discussed in [8], have also shown promise in HAR, outperforming traditional methods like Support Vector Machines (SVM) [9, 10]. Research has explored the integration of additional sensors like GPS and magnetometers [11, 12], demonstrating enhanced recognition capabilities for activities such as walking and jogging. Recent efforts focus on deep learning models like CNN and Long Short-term Memory (LSTM), which integrates temporal information without explicit feature extraction [13, 14]. Variants like Bi-LSTM [15] have extended LSTM's capabilities by incorporating bidirectional learning, achieving high accuracies up to 95% [16].

Comparative studies between CNN and LSTM variants [17, 18] indicate both techniques are suitable for short-term activities, with CNN favored for its computational efficiency [19]. Other research emphasizes hybrid models combining different deep learning architectures to leverage the strengths of each method [20, 21]. Despite advancements, challenges persist regarding device orientation and placement variability [22, 23], which significantly impact HAR accuracy. Addressing these issues remains crucial for real-world applications.

Studies such as [24, 25] have further explored the application of deep learning in recognizing more complex activities, utilizing larger datasets to improve model robustness. The potential for real-time recognition systems has been enhanced through research into lightweight models [26, 27], which allow for efficient processing on mobile devices. Additionally, attention mechanisms integrated into LSTM architectures have been proposed to enhance performance in HAR tasks [28, 29].

Sensor fusion techniques [30, 31, 59] have gained traction, allowing for better recognition accuracy by combining data from multiple sources. This approach is particularly effective for activities that require a nuanced understanding of motion [32, 33]. Research also highlights the role of context in improving HAR systems, with studies focusing on the influence of environmental factors [34, 35]. The exploration of unsupervised learning methods for HAR, as seen in [36, 37], offers promising avenues for future research, potentially reducing the dependency on labeled data.

Challenges remain in recognizing complex human activities, especially in varied settings, as noted in studies [38, 39]. The importance of feature engineering in improving model performance has been emphasized in [40, 41, 58], which suggests that manually crafted features can still play a vital role alongside deep learning techniques. Moreover, studies like [42, 43] emphasize the need for standardization in HAR datasets to facilitate better comparison across different models and approaches.

Emerging trends in HAR research include the application of transfer learning [44, 45], which allows models trained on one dataset to perform effectively on another, addressing data scarcity issues. The impact of sensor placement on HAR accuracy has been studied [46, 47], underscoring the need for careful consideration in practical applications. Advances in privacy-preserving techniques for HAR, as discussed in [48, 49], are critical in addressing user concerns while maintaining performance. Finally, future directions in HAR research point toward leveraging more diverse and inclusive datasets to improve generalizability across different populations [50, 51], while also considering ethical implications [52, 53].

The integration of Internet of Things (IoT) devices into HAR frameworks is becoming increasingly prevalent, with studies showing how connected sensors can enhance data collection and processing [54, 55]. This trend is supported by advancements in edge computing, which facilitate real-time processing and decision-making [56, 57]. Overall, the landscape of HAR continues to evolve, driven by innovative methodologies and a deeper understanding of human behaviors.

Experiments Setup:

LSTM networks – ordinarily just called "LSTMs", were introduced by Hoch Reiter & Schmid Huber, (LSTM) networks are a improved version of recurrent neural networks, the main feature being LSTM to remember previous data in memory [39, 54]. LSTM is well suited to predict time series and classify processes. In standard RNNs, this repeating module will have a very simple structure, such as one single layer of tanh, as shown in Figure 2.

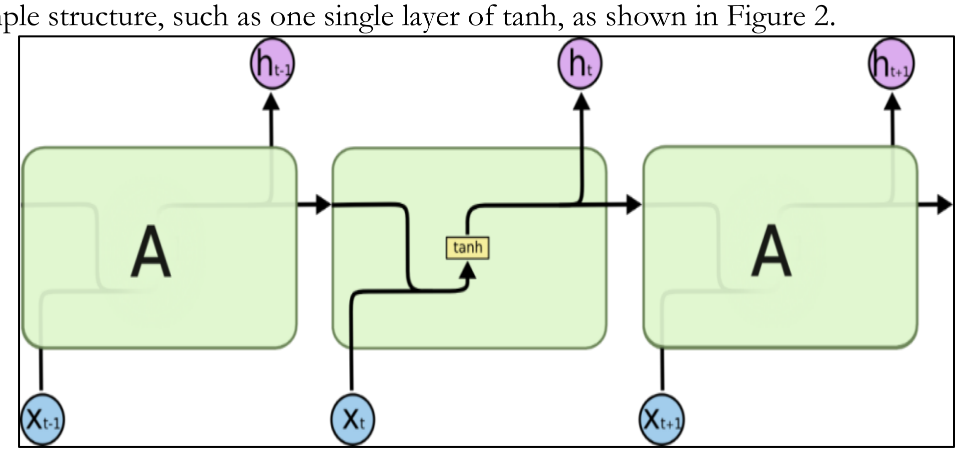

Figure 2. RNN Repeating Module Layer

LSTM has a different module of repeating structure. There are four neural networks instead of single. They interact with each other in different ways as shown in Figure 3.

Cell state is the key of LSTM. The horizontal line in the diagram below is the conveyer belt. Its run straight with linear interaction. It is the easy way for information to flow along without any changes. The ability of the LSTM, wisely controlled by structures called gates, is to expel or add data information to the state of the cell. [50, 51]. For the data to pass through, gates are the only route. They consist of a layer of sigmoid neural network and a point wise multiplication operation.

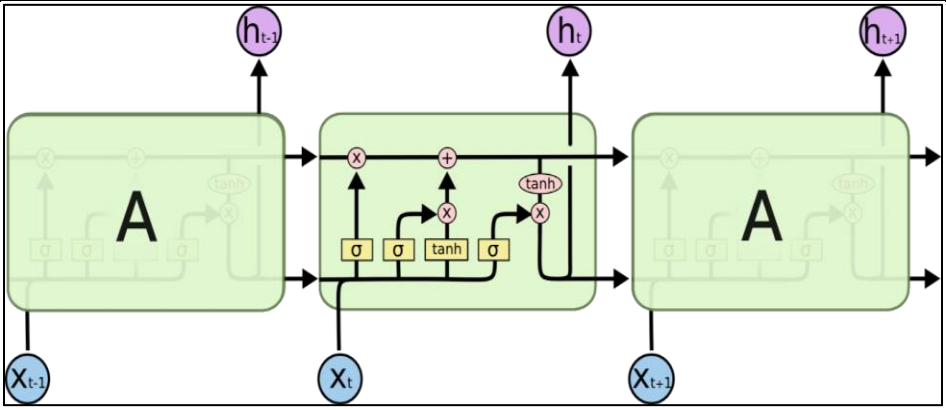

Figure 3. Interacting Layers

Sigmoid layer output numbers are the number between zero and one [40]. The degree to which each element should be allowed through is defined in this layer. The value of zero means, "let nothing through," while a value of one means "let everything through!" There are three gates of LSTM to control and protect the state of cell Figure 4 shown.

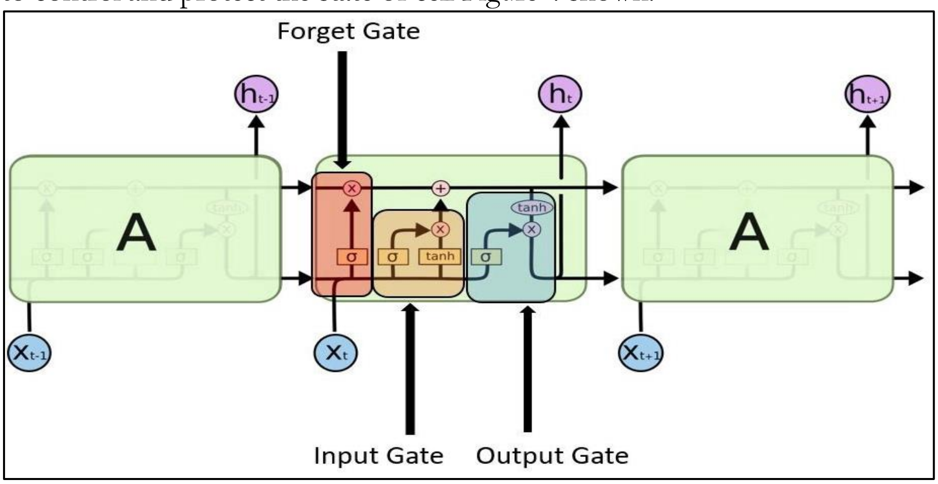

Figure 4. Gates of LSTM

In the first step, the Input Gate finds which data value should be used to change the memory. 0,1 the sigmoid selected to let in. In addition, tanh work provides weighting to the values that are passed selecting their significance level from -1 to 1.

$$i_t = \sigma \left(W_i \, . [h_t - 1 \, , x_t \,] + \, b_i \right)$$

$$\breve{C}_t = \tanh(W_C \, . \ [h_{t-1} \, , x_t \,] + b_C \,)$$

The sigmoid feature selects what information to discard from the block on Forget gate level. It appears at the previous state (ht-1) and input content (xt) and outputs a number in the cell state Ct-1 between 0 (forget this) and 1 (keep this) for each number.

$$f_t = \sigma \left(W_f \, . [h_{t-1} \, , x_t \,] + \, b_f \,\right)$$

The output is dependent on the block's input and memory. The tanh function gives the transmitted values weight, determines their significance level ranging from -1 to 1 and multiplies them by the production of Sigmoid.

$$O_t = \sigma \left(W_\circ [h_{t\,-1} \, , x_t \,] + \, b_\circ \,\right)$$

$$h_t = O_t * \tanh \, (C_t \,)$$

Long Short-Term Memory models are exceptionally good models of the time series data. As the studies focused on recognition of human activities by getting the data from the sensors of the Smartphone which is a time series data. A LSTM module has five major components that enable the modeling of both long-term and short-term data.

Cell State:

This means the cell's interior memory, which stores both long-term memory and short-term memory.

Hidden State:

This knowledge refers to the estimated output state of the current input with respect to the previous hidden state and the current input of the cell, which is eventually used to determine the future output.

Input Gate:

The sum of information from the current input to the cell state is chosen.

Forget Gate:

Decide how much information flows into the current cell state from the current input and the earlier cell state.

Output Gate:

Decide the information rate from the current cell state to the hidden state, so that only short-term memories or long-term memories can be selected, if necessary, by LSTM. In the LSTM portion, details of all steps are given.

Data Generator:

To train the model, a data generator is introduced first. This generator of data has a technique called unrolled lots. This sends out a series of numb unrolling batches of sequentially collected input data. In this study, the data size of each batch is 1024. A parallel output batch has every batch of input data.

Defining Parameters of the LSTM and Regression Layer:

Two layers of LSTM are taken and one layer of linear regression, represented by w and b. This took the previous LSTM cell output and outputs the forecast for the next step of the time. To summarize the two LSTM Cell objects, the Multi RNN Cell in Tensor Flow are used. In addition, LSTM cells are introduced for dropout, as they increase efficiency and decrease over fitting.

Parameters Setting in Training Long Short-Term Memory:

The LSTM model was trained with specific parameters, as outlined in Table 1. These include a timestamp of 200, two fully connected layers with ReLU activation, a learning rate of 0.0025, and a batch sample size of 1024.

Table 1. Parameters Setting in Training Long Short-Term Memory

Parameters	Values
Time stamp	200
Fully connected layers	2
Function	Relu
Learning rate	0.0025
Sample of batch	1024

Results and Analysis:

In experiments, the LSTM algorithm was trained on multiple datasets, with 50 epochs per training session. The analysis of results includes accuracy and evaluation graphs (see Figures 5-9), along with the confusion matrices for each dataset. The classification of activities was conducted using data from sensors (accelerometer, gyroscope, magnetometer) mounted on a smartphone, achieving high precision. These results underscore the effectiveness of LSTM in improving the accuracy of HAR.

Pamp2 Results:

Table 2 shows the accuracy for different sensors in the PAMAP2 dataset, with the highest accuracy achieved when combining accelerometer, gyroscope, and magnetometer data. The evaluation graphs for this dataset are presented in Figures 5 and 6, showcasing the LSTM model's performance across sensor combinations.

Table 2. Result of PAMAP2

Sensors	Accuracy
Accelerometer	0.948
Gyroscope	0.827
Magnetometer	0.840
Accelerometer + Gyroscope + Magnetometer	0.964

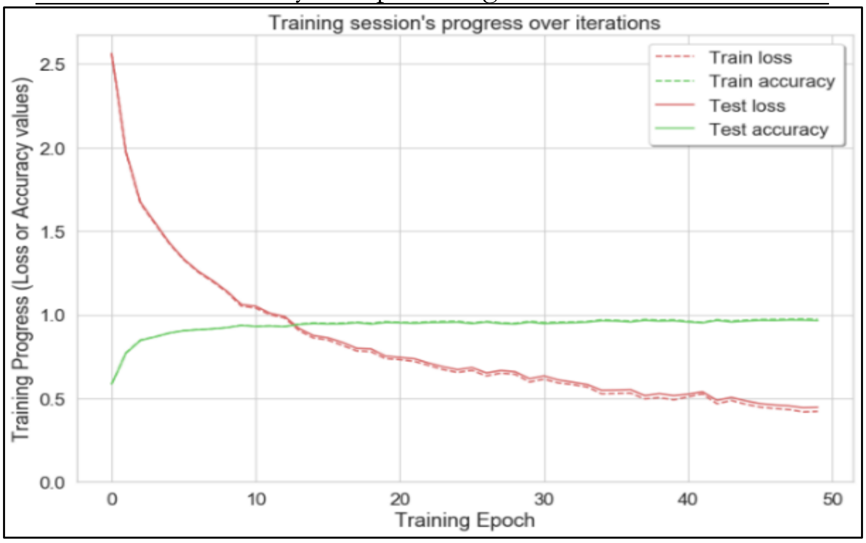

Figure 5. Evaluation Graph of Combine Sensor of PAMAP2

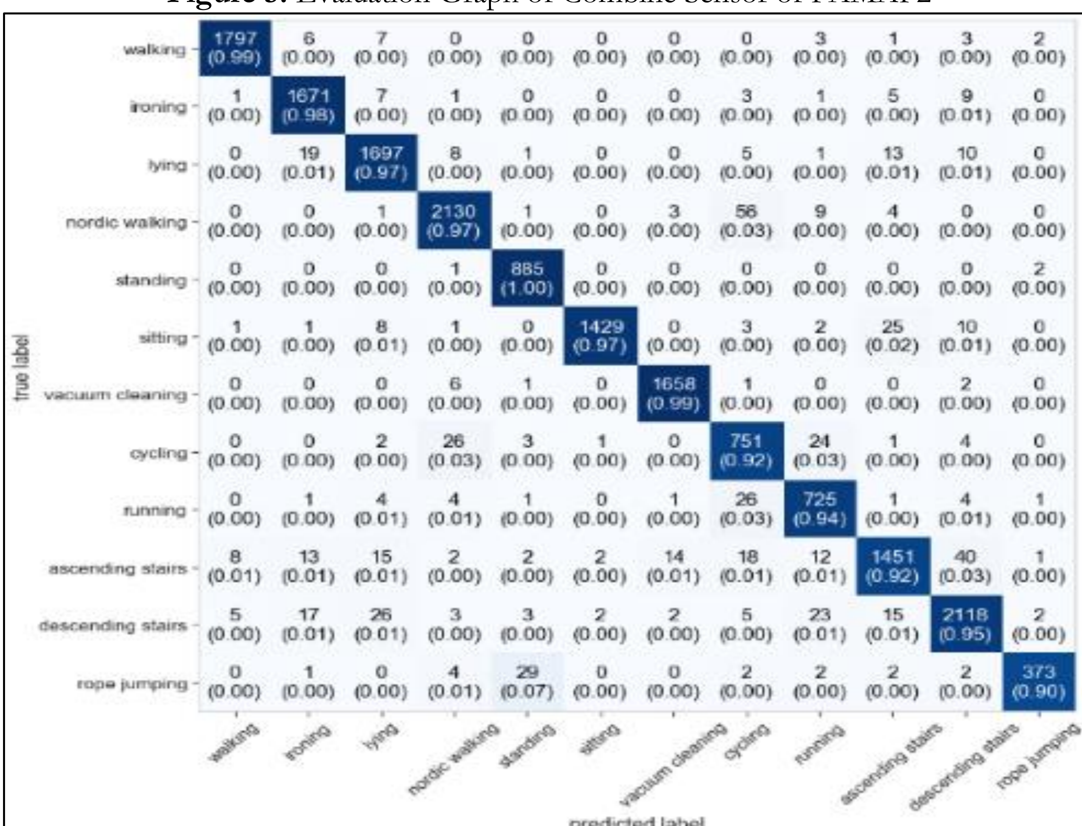

Figure 6. Confusion matrix and evaluation graph of pamp2

Complex Human Activites Recogntion Dataset Results:

The CHAR dataset was evaluated using different sensors, as outlined in Table 3. The highest accuracy of 0.982 was achieved with a combination of accelerometer, gyroscope, and magnetometer. The confusion matrix and evaluation graph for this dataset are illustrated in Figures 7 and 8.

Table 3. CHAR Dataset Results

Sensors	Accuracy
Accelerometer	0.942
Gyroscope	0.898
Magnetometer	0.890
Accelerometer + Gyroscope + Magnetometer	0.982

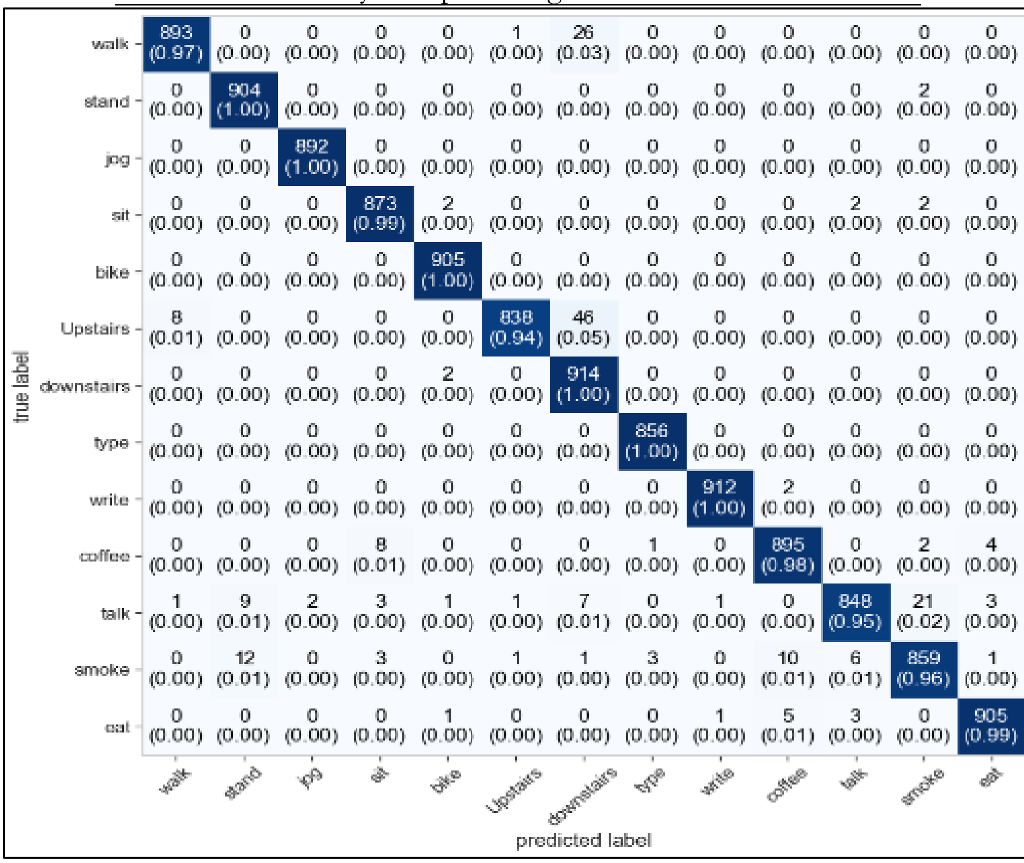

Figure 7. Confusion matrix and evaluation graph of CHAR Dataset

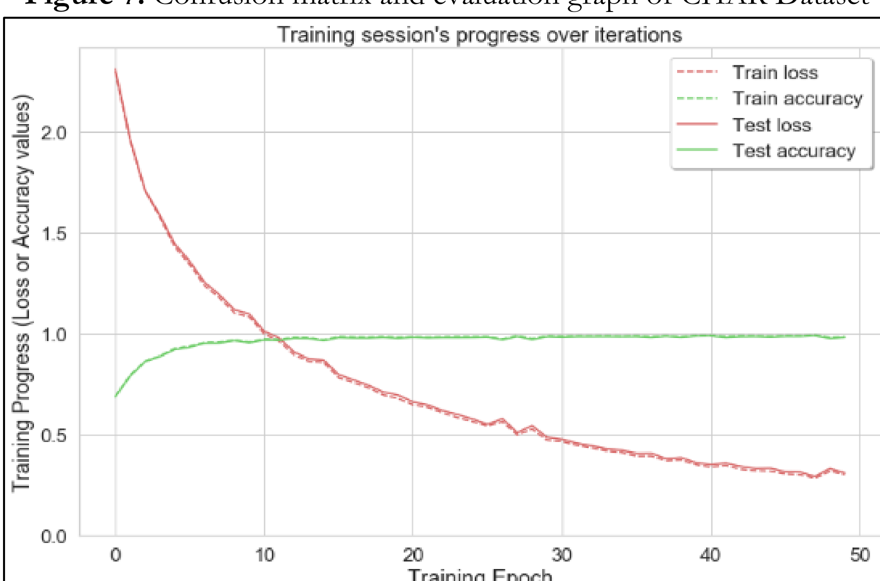

Figure 8. Evaluation graph of Complex Human Activities Dataset

WISDM Dataset Results:

The WISDM dataset was analyzed for activity recognition using an accelerometer, achieving an accuracy of 0.98, as presented in Table 4. The confusion matrix and evaluation graph for WISDM are available in Figures 9 and 10.

Table 4. WISDM Dataset Results

Sensors	Accuracy
Accelerometer	0.98

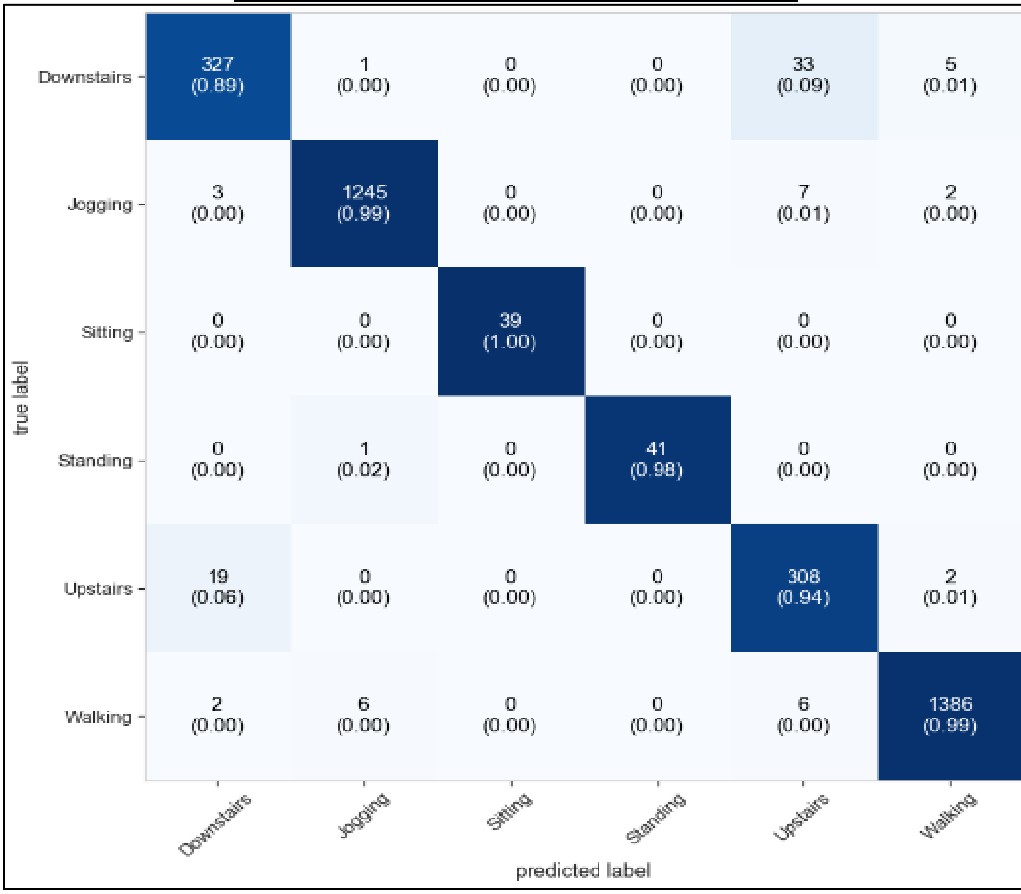

Figure 9. Confusion matrix and evaluation graph of WISDM Dataset

Figure 10. Evaluation graph of Wisdm Human Activities Dataset

Conclusion and Future Work:

The advancement of technology is to make any device intelligent, wherever possible, in our world. Recognition of human activity has newly become an important part of monitoring activities in different areas such as life care from physical damage, childcare, nursing, rehabilitation, health assistance and smart homes to make a more intelligent environment for people. There are broadly two categories of human activities. Simple types of activities like sitting, walking, and standing, it also includes walking downstairs or walking upstairs, are called simple human activities. On the other hand, Complex human activities, includes some kind of work along with simple activity; such as drinking coffee, working on computer, driving a car, smoking, etc. The focus of this study is to recognize complex human activities using LSTM approach.

In this paper, a multilayer LSTM is used on publicly available datasets, including, PAMAP2, Complex human Activities, and WISDM for the recognition of complex activities using single and multiple sensors. The proposed approach showed that satisfactory results can also be achieved using single sensor data instead of multiple sensors. The results showed that Accelerometer sensor achieve higher accuracy when we compare these results with other sensors, but using multiple sensors increased the accuracy of each activity. The proposed approach achieves high accuracy when compared with CNN and other traditional machine learning approaches. In future, this model can be used for real-time complex human activity recognition with Smartphone-based applications.

Objective of the Study:

The objective of this study is to explore the effectiveness of Long Short-Term Memory (LSTM) networks for Complex Human Activity Recognition (CHAR) using mobile phone sensors. It aims to evaluate the performance of LSTM models in recognizing complex human activities with varying sensor combinations (accelerometer, gyroscope, magnetometer) and to assess whether accurate recognition can be achieved using a single sensor, particularly the accelerometer, compared to multiple sensors.

Novelty Statement:

This research uniquely addresses the challenge of Complex Human Activity Recognition (CHAR) using LSTM networks, moving beyond basic activity recognition. Unlike traditional machine learning methods, including CNNs, this study demonstrates how LSTM can simplify sensor requirements while maintaining high accuracy, offering a more efficient solution for recognizing complex human activities with minimal sensor data.

Discussion:

The study demonstrates that Long Short-Term Memory (LSTM) networks are highly effective in recognizing complex human activities using sensor data from mobile devices. The results show that a single accelerometer sensor can achieve reasonable accuracy (94%) for activity recognition, which suggests that relying on fewer sensors can still yield robust performance. However, when additional sensors like gyroscopes and magnetometers are incorporated, the accuracy improves further (up to 98%), though at the cost of increased resource usage, such as power and computational overhead. This trade-off highlights the practical advantage of LSTM in optimizing sensor usage for resource-constrained environments. Moreover, the study indicates that LSTM networks outperform traditional machine learning models, such as CNNs, particularly in handling sequential and complex activity data. The use of LSTM's memory capabilities allows for a more nuanced understanding of human activities, making it suitable for applications that require real-time and accurate behavior analysis, such as health monitoring and smart home environments. Thus, LSTM offers a scalable and efficient approach to Complex Human Activity Recognition (CHAR) while reducing the dependency on multiple sensors, making it a cost-effective solution for real-world applications.

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