**Literature Survey on Human Activity Recognition Using RNN and LSTM**

#### **Introduction**

Human Activity Recognition (HAR) is an application that deals in classifying human activities (walking, sitting, and standing) using data from smartphone sensors (accelerometer and gyroscope). This project aims to explore the application of machine learning techniques, including ensemble methods like Voting Classifiers and deep learning models using feedforward neural networks. By building a system that can accurately recognize various human activities, this project can contribute to areas such as healthcare, fitness tracking, and human-computer interaction. **As an advancement to the current approach, we are exploring Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks as a future improvement.** These models are prominent due to their ability to handle sequential data, making them ideal for recognizing activities that depend on time-series data.

#### **Recurrent Neural Networks (RNNs) for HAR**

##### **Overview**

Recurrent Neural Networks (RNNs) are a class of neural networks that process sequential data by maintaining a hidden state that evolves over time. Unlike traditional feedforward neural networks, RNNs have loops in their architecture, allowing information from previous time steps to influence current predictions. This feature is particularly beneficial for tasks involving time-series data like HAR, where the activity being recognized depends on the history of previous activities.

##### **Applications in HAR**

RNNs have been applied to various HAR tasks, where accelerometer and gyroscope data from wearable devices are used to classify activities such as walking, running, sitting, or lying down. A study by Anguita et al. (2013) demonstrated the effectiveness of RNNs in HAR tasks, where they employed a feature extraction process from sensor data followed by an RNN model to classify six different activities. Their results showed that RNNs could capture temporal dependencies in activity patterns and achieve promising accuracy.

##### **Challenges**

Despite their advantages, RNNs have limitations when dealing with long-term dependencies. The vanishing gradient problem, a common issue in standard RNNs, arises during backpropagation when gradients become very small, making it difficult for the network to learn long-range dependencies. This problem becomes more pronounced as the sequence length increases, which is often the case in HAR tasks that involve continuous sensor data over long periods.

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##### **Variants of RNNs**

To address the vanishing gradient problem, several variants of RNNs have been developed. These include Gated Recurrent Units (GRUs), which offer a simpler architecture compared to LSTMs, and bidirectional RNNs, which process data in both forward and backward directions to capture additional context. However, these models still face challenges in capturing very long-range dependencies, which has led to the widespread adoption of LSTM networks for HAR tasks.

#### **Long Short-Term Memory (LSTM) for HAR**

##### **Overview**

Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), are a type of RNN designed to overcome the limitations of traditional RNNs. LSTMs contain memory cells and gating mechanisms (input, forget, and output gates) that control the flow of information through the network. These mechanisms enable LSTMs to retain information over long periods and avoid the vanishing gradient problem, making them particularly suitable for tasks involving long-range dependencies, such as HAR.

##### **Applications in HAR**

LSTMs have become the dominant approach for HAR due to their ability to model temporal dependencies more effectively than traditional RNNs. Reyes-Ortiz et al. (2016) used LSTMs to classify activities from sensor data, outperforming other machine learning techniques like Support Vector Machines (SVMs) and Random Forests. The LSTM model was able to maintain contextual information over longer sequences, allowing for more accurate classification of activities like walking, running, and cycling.

LSTMs have also been successfully applied to complex HAR tasks involving multi-modal data. For instance, Ofli et al. (2016) applied LSTM networks to the UCI HAR dataset, which consists of accelerometer and gyroscope data, and demonstrated superior performance compared to traditional methods.

##### **Advantages over RNNs**

The primary advantage of LSTMs over traditional RNNs lies in their ability to capture long-term dependencies in sequential data. The gating mechanisms in LSTMs allow the network to retain information for longer time intervals, which is essential in recognizing activities that unfold over extended periods. For example, in HAR tasks where an activity might be interrupted or overlap with another, LSTMs can effectively retain the relevant context, leading to better performance.

Moreover, LSTMs are less prone to the vanishing gradient problem, which allows them to maintain stable learning and provide more reliable predictions when trained on large datasets with long sequences.

##### **Hybrid Models**

In recent research, LSTMs have been integrated with other deep learning models, such as Convolutional Neural Networks (CNNs), to improve the feature extraction process and enhance performance. CNN-LSTM hybrid models are particularly effective in applications where sensor data involves both spatial and temporal features, such as in multi-modal HAR tasks that include both image and sensor data. For example, Hussain et al. (2018) proposed a CNN-LSTM model for human activity recognition from wearable sensor data, where the CNN component extracted spatial features, and the LSTM component modeled the temporal relationships, leading to improved classification accuracy.

#### **Comparison of RNN and LSTM in HAR**

##### **Performance Comparison**

While both RNNs and LSTMs are used in HAR, LSTMs consistently outperform standard RNNs in terms of accuracy and generalization. Iqbal et al. (2017) compared the performance of traditional RNNs and LSTMs for activity recognition using accelerometer data. They found that LSTMs achieved higher classification accuracy, especially in cases where the activity sequence involved long-term dependencies, such as transitioning between different activities.

RNNs, while computationally cheaper and easier to implement, struggle to capture long-range dependencies in sensor data, which is a crucial aspect of HAR tasks. LSTMs, on the other hand, provide better performance due to their ability to retain relevant temporal information over longer periods.

##### **Real-time HAR**

One of the key challenges in deploying HAR systems in real-world applications, such as healthcare monitoring or fitness tracking, is real-time performance. LSTM networks, due to their complex architecture, can be computationally expensive, which may limit their applicability in real-time scenarios, especially on resource-constrained devices like smartphones or wearables.

To address this, various optimization techniques, including pruning, quantization, and model distillation, have been explored to reduce the computational overhead of LSTM models without significantly sacrificing accuracy. These techniques are particularly important in edge-based HAR systems that need to operate efficiently on devices with limited processing power.

#### **Challenges and Future Directions**

##### **Variability in Sensor Data**

One of the main challenges in HAR is the variability of sensor data across different individuals. People may perform the same activity in different ways, leading to variations in the sensor readings. This variability can reduce the generalization ability of the model. To address this, researchers are exploring techniques like transfer learning, where models trained on one dataset are fine-tuned on another dataset to improve performance across different subjects.

##### **Multi-modal HAR**

Another exciting direction for future research is multi-modal HAR, where data from multiple sensors, such as accelerometers, gyroscopes, and even video or audio inputs, are combined to improve activity recognition. Multi-modal systems can provide richer contextual information, which can lead to better recognition accuracy, especially in ambiguous or overlapping activity scenarios. LSTM networks can be extended to handle multi-modal data by incorporating attention mechanisms or by using hybrid models that combine different deep learning architectures.

#### **Conclusion**

Human Activity Recognition using RNNs and LSTMs has shown significant advancements, with LSTMs emerging as the preferred choice due to their ability to capture long-term dependencies in sequential data. While RNNs offer a simpler approach, LSTMs' gating mechanisms allow them to retain critical information over longer sequences, making them more effective for HAR tasks. Hybrid models that combine LSTMs with other techniques, such as CNNs, are also gaining popularity due to their enhanced feature extraction and classification capabilities. Future research will focus on addressing challenges such as real-time processing, variability in sensor data, and multi-modal integration, which will further enhance the effectiveness and applicability of HAR systems.

### **Bibliography**

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