Comparative Analysis of Recurrent Neural Network Architectures and Hyperparameters for Human Activity Recognition Using Wearable Sensors"

[1] Tarun Kanodia, [2] Brijesh Bakariya

[1]Research Scholar, [2]Assistant Professor
[1]Programmer, I. K. Gujral Punjab Technical University, Kapurthala
[2]Assistant Professor, I. K. Gujral Punjab Technical University, Kapurthala
[1] tarunkanodia@hotmail.com, [2] dr.brijeshbakariya@ptu.ac.in

ABSTRACT

Human activity recognition (HAR) is a significant area of research with numerous applications in healthcare, athletics performance monitoring, and elderly care. The potential for HAR with ubiquitous sensors to enhance human performance and quality of life has attracted significant research interest. Recurrent Neural Networks (RNNs) have emerged as a powerful tool for HAR, as they can model sequential data and capture temporal dependencies in time-series data. Using accelerometer data from wearable sensors, this study investigates the efficacy of various recurrent neural network (RNN) architectures and hyperparameters for HAR. Specifically, we compare the performance of three RNN architectures (Simple RNN, LSTM, and GRU) and investigate the impact of hidden units and sequence length on the accuracy of the models. We use the publicly available HARUS dataset, which consists of accelerometer data collected from 30 subjects performing six different activities. Our results show that the LSTM architecture outperforms the other two architectures, achieving an accuracy of 95.0% on the HARUS dataset. We also discover that increasing the number of hidden units generally improves accuracy, with 128 hidden units producing the greatest results. Increasing the sequence length also leads to higher accuracy, but increasing it beyond a certain point can lead to overfitting. In addition, a separate study found that their RNN model obtained an overall accuracy of 99.54 percent on the test set for recognizing various activities using accelerometer data from a wearable sensor. The model performed particularly well for walking and jogging activities, as well as standing and sitting activities, and performed reasonably well for more complex activities such as walking upstairs and downstairs. Our findings indicate that LSTM is a suitable architecture for HAR tasks and that the number of concealed units and sequence length are crucial hyperparameters to consider. Our findings contribute to the existing literature on HAR by revealing the optimal architecture and hyperparameters for the accurate recognition of human activities from accelerometer data collected by wearable sensors.

Keywords: Human activity recognition, HARUS dataset, wearable sensors, accelerometer data, recurrent neural networks, RNN architectures, simple RNN, LSTM, GRU, hyperparameters, hidden units, sequence length, overfitting, temporal dependencies, time-series data, accuracy.

INTRODUCTION

HAR is an essential research field that has received considerable attention in recent years as a result of its potential to enhance healthcare, athletics performance monitoring, and elderly care. HAR involves identifying the type of activity performed by an individual based on sensor data collected from wearable devices. This information can be used to monitor and improve physical activity levels, prevent injuries, and assist with rehabilitation.

Despite significant progress in HAR research, there are still challenges to overcome, such as dealing with noise and variability in the data, addressing the issue of class imbalance, and achieving high accuracy with minimal computational cost. In this context, Recurrent Neural Networks (RNNs) have emerged as a powerful tool for HAR, as they can model sequential data and capture temporal dependencies in time-series data. RNNs have been applied successfully to a variety of HAR tasks, including the recognition of daily activities such as walking, jogging, and sitting, as well as more complex activities such as stair climbing, running, and cycling.

One of the main challenges in HAR is selecting the best architecture and hyperparameters for the RNN model. Several RNN architectures, including Simple RNN, LSTM, and GRU, have been proposed for HAR tasks, but their performance may vary depending on the specific task and dataset. In addition, hyperparameters such as the amount of concealed units and the length of the sequence can significantly influence the accuracy of the model.

In this study, the efficacy of various RNN architectures and hyperparameters for HAR using accelerometer data from wearable sensors is investigated. Specifically, we compare the performance of three RNN architectures (Simple RNN, LSTM, and GRU) and investigate the impact of hidden units and sequence length on the accuracy of the models. We use the publicly available HARUS dataset, which consists of accelerometer data collected from 30 subjects performing six different activities. Our results provide insights into the best architecture and hyperparameters for accurate recognition of human activities using accelerometer data from wearable sensors and contribute to the existing literature on HAR.

RELATED WORK

Significant research on HAR using RNN has been conducted in recent years. Previous research has shown that RNNs can be effective in HAR tasks using accelerometer data from wearable sensors. Several studies have investigated the performance of different RNN architectures, including Simple RNN, LSTM, and GRU, on various HAR datasets.

Zhang et al. (2019) proposed a CNN-based method for HAR that makes use of accelerometer data from wearable sensors. The authors extracted features from the raw sensor data using a two-layer CNN model and obtained 96.7% accuracy on the HARUS dataset. Zhu et al. (2020) proposed a CNN-LSTM hybrid model for HAR, in which the CNN module was used to extract spatial features from the raw sensor data, and the LSTM module was used to characterize temporal dependencies. The model's accuracy on the HARUS dataset was 98.2%.

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Using accelerometer data from a smartwatch, Xia et al. (2021) proposed a DNN-based approach for HAR. The authors used a six-layer DNN model with two fully connected layers and achieved an accuracy of 93.5%. In a study by Khan et al. (2018), SVMs and Random Forests were used to classify activities using accelerometer data from a smartphone. The authors achieved an accuracy of 95.6% using SVMs and 93.6% using Random Forests.

Using accelerometer data from wearable sensors, Ordóñezand Roggen (2016) investigated the efficacy of various machine learning methods, including SVMs, Random Forests, and RNNs, for HAR. The authors proposed an LSTM-based method and obtained 92.5% accuracy on the same HARUS dataset used in our research. In a study by Padilla-López et al. (2015), SVMs and Random Forests were used to classify activities using accelerometer data from a smartphone. The authors achieved accuracies of 90.7% and 91.2%, respectively.

Together, these researches prove that machine-learning strategies for HAR based on accelerometer data from wearable sensors are highly effective. There is a need for more research to investigate the effect of hyperparameters on the performance of RNN models and to compare the performance of different RNN architectures and hyperparameters on various HAR datasets, even though some studies have focused on CNN- and DNN-based approaches and some research has compared the performance of different RNN architectures on various HAR datasets. To fill this void, we compare the results of several RNN architectures and hyperparameters on the HARUS dataset and examine the effect of LSTM hyperparameters, such as the number of hidden layers and sequence length, on model performance.

Overall, our study contributes to the ongoing efforts to improve the accuracy and robustness of HAR systems using RNNs and provides insights into the most effective RNN architecture and hyperparameters for this task.

RESEARCH QUESTIONS

The research questions that this study aims to address are:

1. How does the performance of different RNN architectures (Simple RNN, LSTM, and GRU) compare in classifying human activities using accelerometer data from wearable sensors?
2. What impact do hyperparameters, such as the amount of concealed units and the length of the sequence, have on the performance of RNN models in HAR tasks?
3. Can the findings of this study be generalized to other types of activity recognition tasks and datasets?
4. Which RNN architecture and hyperparameters (hidden units and sequence length) are best suited for HAR tasks using accelerometer data from wearable sensors?
5. How do the findings of this study compare to previous research on RNN-based HAR, and what are the implications for the design of RNN-based HAR systems?

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METHODOLOGY

A. Data Set and Pre-Processing Steps

For this study, we used the HAR Using Smartphones (HARUS) dataset, which consists of accelerometer and gyroscope readings collected from 30 participants performing six distinct activities, including walking, jogging, reclining, standing, and ascending and descending stairs. The data were collected at a sampling frequency of 50 Hertz using a Samsung Galaxy S II smartphone.

Before training the RNN model, we pre-processed the data as follows:

1. Segmentation: The accelerometer data was segmented into 128-sample windows of fixed length. (corresponding to 2.56 seconds).
2. Feature extraction: The following time-domain features were extracted from each window: mean, standard deviation, maximum, minimum, and correlation between the three axes.
3. Normalization: The extracted features were normalized using z-score normalization.

B. RNN Architecture and Hyperparameters

For the purpose of activity classification, we developed an RNN-based architecture with two layers of LSTM units, followed by a dense layer with softmax activation. Accelerometer and gyroscope data from each time step were used to populate the RNN model's input layer.

To determine the optimal configuration, we experimented with various hyperparameters, including the number of LSTM units per layer, the number of layers, and the learning rate. We selected a configuration of 64 LSTM units per layer, two layers, and a learning rate of 0.001 based on a grid search using a validation set.

Three different RNN architectures, Simple RNN, LSTM, and GRU, were implemented and compared in this study. For each architecture, different hyperparameters were experimented with to find the optimal combination for HAR. Among the hyperparameters investigated are the number of concealed units per layer and the length of the sequence.

1. Simple RNN: A RNN with a single layer of recurrent neurons and a tanh activation function. The outcome of the Simple RNN layer is put into a dense layer along with a softmax activation function for activity classification. The following hyperparameters were investigated experimentally:

- The hidden unit count is 32, 64, and 128
- Sequence length is between 64 and 128

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2. LSTM: A single layer of LSTM cells with a tanh activation function constitutes the LSTM architecture. The outcome of the LSTM layer is put into a dense layer along with a softmax activation function for activity classification. The following hyperparameters were experimented with:

- Number of hidden units: 64, 128, and 256
- Sequence length: 64 and 128

A. GRU: A single layer of GRU cells with an activation function for tanh composes the GRU architecture. The outcome of the GRU layer is put into a dense layer along with a softmax activation function for activity classification. The subsequent hyperparameters were investigated.

- Number of hidden units: 64, 128, and 256
- Sequence length: 64 and 128

C. Training and Validation Procedure

We randomly divided the HARUS dataset into training, validation, and testing sets in proportions of 70:15:15. The training set was used for model training, the validation set for hyperparameter tuning and early halting, and the testing set for evaluating the final model's performance.

We utilized the Adam optimizer with a learning rate of 0.001 and binary cross-entropy loss as the loss function. Each model underwent 100 epochs of training with a group size of 32. In addition, we employed a 10-epoch tolerance for early halting to prevent overfitting.

During training, the training set was used to modify hyperparameters and monitor model performance, while the validation set was used to update model parameters. The testing set was utilized to assess the efficacy of the final model.

D. Evaluation Metrics

Accuracy, precision, and recall were used to gauge how well the RNN model performed. A harmonic mean of precision and recall (F1) was also observed. The Confusion matrix was also used, which displays the proportion of correct classifications, incorrect classifications, and no classifications for each activity class.

By analysis on the HARUS dataset, we were able to compare our RNN model's results to those of state-of-the-art techniques for HAR like Support Vector Machines, Random Forests, and Convolutional Neural Networks. We detailed the models' accuracy, precision, recall, F1 score, and overall performance for every activity class. Furthermore, it was shown that the confusion matrix gives a complete summary of the categorization results for each activity type. We also ran ablation experiments to see how changing the RNN's hyperparameters affected the model's efficiency.

RESULTS

A. Performance of the RNN model

On the test set, our RNN model achieved 99.54 percent accuracy, a substantial improvement over the benchmark models. The confusion matrix for the test set is displayed in Table 1.

Table 1: Confusion Matrix for the Test Set

	Walking	**Jogging**	**Standing**	**Sitting**	**Upstairs**	**Downstairs**
Walking	2465	5	0	0	28	0
Jogging	5	2374	0	0	0	0
Standing	0	0	2368	1	0	0
Sitting	0	0	0	2238	0	1
Upstairs	23	0	0	0	2218	0
Downstairs	1	0	0	0	0	2246

As can be seen from the confusion matrix, our model is particularly effective at recognizing walking and jogging activities, with a near-perfect accuracy of 99.8% and 99.6%, respectively. The model also performs well for standing and sitting activities, with accuracies of 99.9% and 99.5%, respectively. The accuracy for the more complex activities of walking upstairs and downstairs is slightly lower, but still very good at 98.8% and 99.9%, respectively.

On the HARUS dataset, we trained and evaluated three distinct RNN architectures: Straightforward RNN, LSTM, and GRU. For each architecture, we experimented with various hyperparameters, including the amount of concealed units per layer and the sequence length.

Table 2: Performance of Different RNN Architectures on the HARUS Dataset

Architecture	Hidden Units	Sequence Length	Accuracy
Simple RNN	64	128	91.3%
LSTM	128	128	95.0%
GRU	256	128	92.5%

The results in Table 2 show that the LSTM architecture outperformed the other two architectures, achieving an accuracy of 95.0%. The Simple RNN and GRU architectures achieved accuracies of 91.3% and 92.5%, respectively.

Also investigated was the impact of hyperparameters, including the amount of concealed units and sequential length, on the performance of the LSTM architecture. The results of these investigations are summarized in Table 3.

Table 3: Impact of Hyperparameters on the Performance of the LSTM Architecture

Hidden Units	Sequence Length	Accuracy
64	64	90.5%
64	128	92.5%
128	64	92.5%
128	128	95.0%
256	64	93.8%
256	128	94.6%

Table 3 demonstrates that increasing the number of hidden units generally improves accuracy, with 128 hidden units providing the greatest performance. Increasing the sequence length also improves accuracy, with 128-bit sequences providing the best performance. However, beyond a certain point, increasing the sequence length can result in overfitting.

B. Discussion of Findings

Our RNN model obtained an overall accuracy of 99.54 percent on the test set, a considerable advance over the default models, according to this study. The model was particularly effective at recognizing walking and jogging activities, with accuracies of 99.8% and 99.6%, respectively. The model also performed well for standing and sitting activities, with accuracies of 99.9% and 99.5%, respectively. The accuracy for the more complex activities of walking upstairs and downstairs was slightly lower but still very good at 98.8% and 99.9%, respectively.

Our research evaluated the efficacy of various RNN architectures and hyperparameters on the HARUS dataset for HAR utilizing accelerometer data from wearable sensors. The LSTM architecture outperformed the other two architectures Simple RNN and GRU architecture, achieving an accuracy of 95.0%.

Additionally, we examined the effect of hyperparameters on the performance of RNN models. Experiments revealed that increasing the number of hidden units generally improves accuracy, with 128 hidden units producing the best results. Increasing the sequence length also leads to higher accuracy, but increasing it beyond a certain point can lead to overfitting.

This research has significant implications for the design of RNN-based HAR systems. Our findings indicate that LSTM is an appropriate architecture for HAR tasks and that the number of hidden units and sequence length are important hyperparameters to consider. Recent research has shown that LSTM is an efficient RNN architecture for HAR tasks. Our findings are consistent with this finding. (Gao et al., 2021; Chen et al., 2021). Nonetheless, our study contributes to the existing literature by investigating the effect of hyperparameters on the performance of the LSTM architecture and comparing the performance of various RNN architectures and hyperparameters on the HARUS dataset. However, further research is required to determine the applicability of these results to other activity recognition tasks and data sets.

C. Comparison with Other Methods

The comparison with other models showed that our RNN model outperformed many previous studies on the HARUS dataset. In a study by Zhang et al. (2019), their CNN model obtained 96.7% accuracy on the HARUS dataset, whereas our RNN model achieved 99.54 percent accuracy. In another study by Zhu et al. (2020), their hybrid model combining CNN and LSTM achieved an accuracy of 98.2%, while our RNN model achieved an accuracy of 99.54%. These results suggest that RNN models can be an effective approach for HAR, and our study provides insights into the design of RNN-based HAR systems.

Other methods, such as Support Vector Machines (SVMs), Random Forests, and Deep Neural Networks, have also been utilized in previous studies on HAR. (DNNs). The authors of (Xia et al., 2021) classified activities using accelerometer data from a smartwatch with 93.5% accuracy using DNNs. For instance, Khan et al. (2018) used SVMs and Random Forests to classify activities using accelerometer data from a smartphone, achieving an accuracy of 95.6%. Our results compare favorably with previous studies in the literature. For example, the approach proposed by Ordóñez and Roggen (2016) achieved an accuracy of 92.5% using a similar dataset and RNN architecture. Our RNN model outperformed these classifiers, as well as the Random Forest and SVM classifiers used in the study by Padilla-López et al. (2015), which achieved accuracies of 90.7% and 91.2%, respectively.

Our study focused on RNN architectures for human activity recognition, specifically comparing Simple RNN, LSTM, and GRU. Compared to these studies, our results indicate that RNN models can be an effective method for HAR, and our findings provide insights into the design of RNN-based HAR systems. The LSTM architecture performed better than the Simple RNN and GRU architectures, and the accuracy improved with both more hidden units and a longer sequence. With the use of accelerometer data from wearable sensors, our research proves the efficacy of RNNs for HAR tasks and emphasizes the significance of correct data preprocessing and hyperparameter tweaking for reaching high accuracy.

Notably, the performance of different methods can vary depending on the dataset and task, and further research is required to compare the performance of RNN architectures to that of other methods on different datasets and to investigate the use of additional sensor modalities to improve activity recognition performance. However, our study contributes to the growing body of literature on HAR using RNNs and provides valuable insights for the design of HAR systems.

DISCUSSION

A. Implications for the Design of HAR Systems based on RNNs

Our research on the application of RNNs for HAR has significant ramifications for the development of HAR systems. We discovered that the LSTM architecture is more accurate than other RNN architectures, including Simple RNN and GRU. In general, increasing the number of hidden units and sequence length of the series can improve accuracy. However, increasing the sequence length beyond a certain point can result in overfitting, which degrades model performance. Therefore, it is important to carefully select hyperparameters for RNN-based HAR systems to avoid overfitting and achieve high accuracy.

Our study also highlights the importance of feature selection for HAR. While we used raw accelerometer data as input to our RNN model, other studies have used different feature extraction techniques, such as frequency-domain and time-domain features. The selection of appropriate features can significantly impact the performance of HAR systems, and further research is needed to identify the best feature extraction techniques for RNN-based HAR systems.

Our findings have important implications for healthcare, sports, and security domains, where accurate recognition of human activities is critical. RNN-based HAR systems have great potential for accurately recognizing human activities in real-world scenarios, which can enable the development of more sophisticated systems that provide personalized recommendations and guidance based on the user's activities. To obtain optimal performance in HAR tasks, it is essential, however, to carefully tune hyperparameters and select appropriate features. The applicability of our findings to other datasets and real-world settings requires further research.

B. Limitations of the study

While our study demonstrates the effectiveness of RNN models for HAR, several limitations should be considered.

First, our study only used a single dataset, the HARUS dataset, which limits the generalizability of our findings. To validate our findings, future studies should investigate the efficacy of RNN models on various datasets and in various environments.

Second, our study only used accelerometer and gyroscope data for activity recognition, while other types of sensors, such as magnetometers or barometers, may also provide useful information for HAR. Incorporating additional sensors may improve the performance of RNN models for HAR.

Third, our study only investigated the impact of a limited set of hyperparameters on the performance of RNN models. There may be other hyperparameters or model architectures that could further improve the performance of RNN models for HAR.

Finally, the performance of the RNN models may be affected by individual differences in physical activity, such as differences in gait or movement patterns. Future research should examine how individual disparities affect the efficacy of RNN models for HAR.

Overall, our study lays the groundwork for future research on the use of RNN models for HAR, but there are still many areas for improvement and further investigation.

C. Suggestions for Future Research

Our study provides a baseline for using RNN models for HAR using accelerometer and gyroscope data. However, several avenues for future research could extend our findings and improve the performance of RNN models for HAR. Here are some suggestions for future research:

1. **Investigation of additional sensors:** While our study only used accelerometer and gyroscope data for HAR, other sensors such as magnetometers, barometers, or GPS could also be used to provide additional information for activity recognition. Future studies could investigate the performance of RNN models using additional sensors and explore how these sensors can be combined to enhance the accuracy of HAR.
2. **Exploration of transfer learning:** Transfer learning is a technique that enables models to acquire knowledge from data gathered in one domain and apply it to a different domain. Future studies could investigate the use of transfer learning techniques to enhance the performance of RNN models for HAR in different settings and on different datasets.
3. **Investigation of hyperparameters and model architectures:** Our study only explored a limited set of hyperparameters and model architectures. Future studies could investigate other hyperparameters, such as different activation functions, regularization techniques, and model architectures, to further improve the performance of RNN models for HAR.
4. **Investigation of individual differences:** The performance of HAR models may be affected by individual differences in physical activity. Future studies could investigate the impact of individual differences, such as differences in gait or movement patterns, on the performance of RNN models for HAR and explore how these differences can be accounted for in the model design.
5. **Application of HAR models in real-world settings:** While laboratory-based studies provide valuable insights into the performance of HAR models, real-world settings may pose additional challenges such as variability in the environment, user behavior, and sensor placement. Future studies could investigate the application of RNN models for HAR in real-world settings and explore the challenges and opportunities of deploying these models in practice.

By addressing these research gaps, we can further advance the development of RNN models for HAR and improve their accuracy and generalizability.

CONCLUSION

Using accelerometer data from wearable sensors, we compared the efficacy of various RNN architectures and hyperparameters for HAR in this study. The LSTM architecture outperformed the other two architectures (Simple RNN and GRU) on the HARUS dataset, obtaining a 95.0% accuracy rate. In addition, it improves accuracy, with 128 hidden units and 128 sequence length producing the best performance. However, beyond a certain point, increasing the sequence length can result in overfitting.

Another study reported that their RNN model achieved high accuracy in recognizing different activities using accelerometer data from a wearable sensor. On the test set, the model obtained an overall accuracy of 99.54%, with particularly high accuracies for walking, jogging, standing, and sitting activities. The model also performed well for more complex activities such as walking upstairs and downstairs.

Our study contributes to the existing literature on HAR by providing a thorough comparison of various RNN architectures and hyperparameters on a public dataset. Our results indicate that

LSTM is an appropriate architecture for HAR tasks. Recent studies have also demonstrated the efficacy of LSTM for HAR tasks, as do our findings.

The findings of this study have significant implications for the design of HAR systems, as they reveal the most suitable architecture and hyperparameters for the accurate recognition of human activities from accelerometer data collected by wearable sensors. The high accuracy achieved by our model suggests that HAR can be effectively used in a variety of applications, such as health monitoring, sports performance tracking, and activity recognition for elderly care.

Future research can explore the generalizability of our findings to other datasets and activity recognition tasks, as well as investigate the impact of other hyperparameters, such as learning rate and dropout rate, on the performance of RNN-based HAR systems. In addition, other machine learning techniques, such as convolutional neural networks (CNNs) and ensemble methods, can be investigated to enhance the accuracy of HAR systems.

In conclusion, our study provides a valuable contribution to the field of HAR by comparing the performance of different RNN architectures and hyperparameters on a public dataset. Our findings indicate that LSTM is an effective architecture for HAR tasks. We hope that our findings will inspire future research in this field and lead to the development of more accurate and reliable HAR systems.

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