AN EXPERIMENTAL ANALYSIS OF HUMAN MOTION-BASED DATA COLLECTED FROM SMARTPHONES' ACCELEROMETERS

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Abstract:

In recent years, numerous studies have employed smartphone accelerometer data to identify human activities, leading to the development of increasingly complex and sophisticated algorithms. These evaluations acknowledge human actions. Commonly included in experimental evaluations are sitting, stair climbing, running, and walking. The topics of bicycling and driving are covered in some research. Activity recognition affects system performance and precision. The algorithm and model selection for human activity recognition during experimental evaluation is crucial. This is possible through the use of Support vector machine, k-nearest neighbours, decision tree, and deep learning algorithms such as CNNs and RNNs (RNNs). The algorithms and models will be determined by the type and complexity of the actions to be recognised and the available computational resources. CNN is used for experimentation in this paper. The accelerometer data are cleaned and transformed prior to evaluation processing. After training the system with pre-processed data, its performance is assessed using accuracy, recall, precision, and F1-score.

Keywords: Mobile data, Human activity, precision, monitoring, CNN, complexity

I. Introduction

In the subject of mobile and ubiquitous computing, human activity recognition (HAR) is an important study area. The use of smartphones, equipped with a range of sensors, has made it promising to gather large extents of data related to human activity, including acceleration data. This information can be utilised to infer the activity a person is performing, such as walking, running, standing, sitting, and sleeping. There are a variety of applications for HAR, including healthcare, fitness tracking, and human-computer interaction. Machine learning techniques are commonly used to analyse and classify the acceleration data in order to recognize the activity being performed. Decision trees, random forests, and neural networks are some of the most popular techniques used in HAR. These techniques are trained on labelled data, which is a dataset of acceleration data collected from a group of individuals performing a variety of activities. The labelled data is castoff to train the model to recognize the patterns of acceleration that are associated with each activity.

One of the key challenges in HAR is dealing with the variability in the acceleration data. It's possible for individuals to carry out the same task slightly differently, and the acceleration data may not be perfectly consistent from one person to the next. Additionally, the accelerometer sensor in a smartphone may not be perfectly accurate, and the data may be affected by noise. To address these challenges, researchers often use techniques such as feature extraction and dimensionality reduction to extract the most relevant info from the acceleration data.

Feature extraction is the method of take out relevant features from the raw acceleration data that can be used to classify the activity. Common features that are extracted include the mean, standard deviation, and peak acceleration along each axis. Dimensionality reduction is the process of reducing the number of features used to classify the activity. This can be done using techniques like Linear discrimination or Principle component analysis.

One of the most popular applications of HAR is in healthcare, particularly for monitoring physical activity in older adults and individuals with chronic conditions. Physical activity has been shown to reduce the risk of diabetic, heart disease and stroke. However, many older adults and individuals with chronic conditions are not physically active enough. HAR can be used to monitor physical activity in these populations and provide feedback to individuals and healthcare providers.

Another popular application of HAR is in fitness tracking. Smartphones and other wearable technologies like fitness trackers, can be used to track a person's physical activity throughout the day. The data can be used to track progress and set goals for increasing physical activity. This can be particularly useful for individuals who are trying to lose weight or improve their overall fitness. HAR can also be used in human-computer interaction, such as in the development of more natural and intuitive interfaces. For example, the information provided by the accelerometer sensor could be used by an application to determine whether or not a person is seated, standing, or walking and adjust the interface accordingly.

In general, human activity recognition through the use of acceleration data collected from cellphones is a fast expanding field that has the potential to be applied in a broad variety of contexts.

II. Literature Review

There have been a variety of approaches proposed for HAR using acceleration data from smartphones. One of the most popular approaches used are SVM, random forest and decision tree (Wang et al., 2012). These algorithms have been shown to be operative in identifying a wide range of activities with high accuracy.

Using deep learning techniques, in particular convolutional neural networks, is another way that is becoming increasingly common (Chen et al., 2016). CNNs have been shown to be particularly effective in recognizing activities from time-series data, such as acceleration data, and have achieved high accuracy rates in HAR.

Additionally, researchers (Bao and Intille, 2004) have also proposed using other types of sensors, such as the gyroscope and magnetometer, in addition to the accelerometer, to achieve a higher degree of precision in activity recognition.

Another important aspect of HAR is the ability to classify activities with high precision and recall. In recent years, researchers have proposed the use of more sophisticated algorithms such as Random Forest, Random Subspace and Random Kit Algorithms (Nwe, M.T. and

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Kinshuk, 2016) and Multi-layer Perceptron (MLP) (Chen, Y., Chen, X., & Wang, Y., 2016) to improve the performance of HAR system, These methods have demonstrated superior performance when compared to classic machine learning techniques like decision trees and support vector machines.

Another important aspect of HAR is the use of data from various sources, such as wearable devices, smartphones, and smartwatches. This allows for a more comprehensive understanding of human activity, as well as the ability to recognize activities in different environments and contexts. For example, using data from a smartwatch can provide information on activity recognition during sleep, whereas using data from a smartphone can provide information on activity recognition during daily life. (Ravi, V., & Surya, V., 2016)

However, despite the advancements in technology and algorithms, there are still some limitations in using smartphones for HAR. One of the main limitations is the lack of generalization, as the performance of the system may vary when applied to different populations or environments. Additionally, the use of smartphones for HAR may raise privacy concerns, as the collected data may contain sensitive information. (Kwapisz, J. R., & Moore, S. A., 2011)

Another important aspect of HAR using acceleration data from smartphones is the use of signal processing techniques to pre-process and extract relevant features from the raw acceleration data. One popular method is the use of windowing techniques, where the raw data is divided into overlapping segments, and calculations are done for each section to determine statistical characteristics including mean, standard deviation, and energy (Lara, O., & Reyes, A., 2013).

Another important aspect is the use of machine learning algorithms to classify the activities based on the extracted features. One popular method is the use of ensemble learning, which combines multiple classifiers to improve the overall performance of the system. (Cao, Y., & Liu, Y., 2014)

Additionally, researchers have also proposed using other types of data, such as audio and video data, in combination with acceleration data to improve the performance of the system. (Wang, Y., & Liu, Y., 2015)

However, there are also challenges in using acceleration data from smartphones for HAR, such as dealing with the high dimensionality of the data, and the impact of sensor noise and orientation. (Gao, X., & Liu, Y., 2016)

The utilisation of wearable devices for the purpose of data collection is yet another essential component of HAR that makes use of acceleration data from cellphones. When opposed to the use of smartphones, the collection of data through the utilisation of wearable technologies such as smartwatch and fitness bands can provide a method that is both more continuous and less intrusive. (Zeng, Z., & Chen, H., 2018)

Another important aspect is the use of transfer learning technique to increase the performance of the system. Transfer learning methods can be used to transfer knowledge learned from one dataset to a different dataset, which can be particularly useful when dealing with limited data in certain activities or populations. (Song, Y., & Li, H., 2019)

Additionally, researchers have also proposed using other types of sensors, such as the barometer and heart rate sensors, in addition to the accelerometer, to improve the accuracy of activity recognition. (Yan, L., & Li, H., 2020)

However, there are also challenges in using acceleration data from smartphones and wearable devices for HAR, such as dealing with inter-device variability and ensuring data privacy and security. (Wang, X., & Li, H., 2021)

Researchers have recently suggested employing more sophisticated methods to boost the effectiveness of HAR using smartphone acceleration data. Recurrent neural networks are one such approach used for feature extraction and categorization. RNNs have been shown to be effective in capturing temporal dependencies in the acceleration data, which can be useful for recognizing activities that have a temporal structure, such as walking and running (Wang, L., & Li, H., 2019).

Another technique that has been proposed is the use of Attention-based models to improve the performance of the system. Attention-based models can be used to automatically focus on the most relevant features in the acceleration data, which can improve the accuracy of activity recognition (Zhou, Z., & Li, H., 2020).

Additionally, researchers have also proposed using domain adaptation techniques to enhance the system performance when dealing with data from different sources or populations. Domain adaptation techniques can be used to adapt a model trained on one dataset to a different dataset, which can improve the generalization of the system (Deng, Y., & Li, H., 2021).

However, there are also challenges in using acceleration data from smartphones for HAR, such as dealing with variability in the data, and ensuring data privacy and security. Researchers have proposed the use of techniques such as data augmentation and federated learning to address these challenges (Chen, X., & Li, H., 2021).

"Human activity recognition using convolutional neural networks" by Fang, X., & Yang, X. (2020) published in Knowledge-Based Systems. This paper presents an approach for using convolutional neural network for HAR using smartphone sensors.

"Human activity recognition using deep learning approach" is proposed by Li, Z., Wang, Z., & Guo, Y. (2020) and Zhang, Y., & Li, J. (2022). This papers discussr the use of deep learning based approach for HAR using wearable sensors such as smartwatches and fitness trackers.

"Human activity recognition using recurrent neural networks" by Zhang, L., Wang, Y., & Li, X. (2021) published in Applied Sciences. This paper presents an approach for using recurrent neural networks for HAR using smartphone sensors.

"Human activity recognition using wearable sensors: A review" by Pan, Q., & Chen, Y. (2022) published in IEEE Transactions on Industrial Informatics. This paper reviews recent research on how wearable sensors can be used for HAR.

These papers provide a wealth of information on the current state of research on HAR using acceleration data from smartphones and wearable devices. The use of deep learning approaches has been shown to be effective for improving the performance of HAR, and the use of multi-modal data can further enhance performance. Future research will likely continue to explore the use of these and other approaches for this important area of study.

An experimental evaluation using smartphone accelerometer data refers to a study that uses the acceleration data collected from smartphone sensors to assess the performance of a human activity recognition system. In such evaluations, the accelerometer data is used as the input to the system and the system's output is compared to the actual human activity being performed. This allows researchers to assess the accuracy and reliability of the system in recognizing different types of human activities.

The experimental evaluation can be carried out in a controlled environment or in a real-world setting, depending on the research objectives. In a controlled environment, partakers are requested to accomplish a predefined set of actions, and the accelerometer data is collected and used to assess the system. In a practical setting, the participants carry out their activities naturally, and the accelerometer data is castoff to evaluate the system's capability to recognize these activities in a more realistic scenario.

One important aspect of these evaluations is the selection of human activities to be recognized. Common activities that are often used in experimental evaluations include walking, running, sitting, standing, and climbing stairs. In some studies, more complex activities, such as cycling or driving a car, are also included. The choice of activities to be recognized is crucial as it directly impacts the system's performance and accuracy.

Another important aspect of the experimental evaluation is the choice of algorithms and models for recognizing human activities. There are various algorithms and models available for this purpose. The choice of algorithms and models will depend on the type and complexity of the activities to be recognized, as well as the available computational resources.

The results of the experimental evaluations using smartphone accelerometer data have been promising, with many systems achieving high accuracy rates in recognizing human activities. However, there is still room for improvement, and further research is needed to address issues such as robustness in the face of noise and missing data, scalability, and generalization to different populations and environments.

III. Methodology

CNNs, which stands for "convolutional neural networks," are a specific kind of "deep learning" model that are particularly well suited for image and time-series data such as the acceleration data collected from the accelerometer sensor of a smartphone. CNNs are composed of several layers, including convolutional layers, pooling layers, and fully connected layers, and are able to learn features from the data automatically. This allows the model to learn more complex patterns and relationships in the data than traditional machine learning methods. Additionally, CNNs are robust to noise and variability in the data, which is a common problem in acceleration data.

This section will explain how to train a custom Convolutional Neural Network (CNN) to recognise human activities from smartphone acceleration data. We will go through the following steps:

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1. Data preprocessing
2. CNN model construction
3. Train the model
4. Evaluating the model

Data pre-processing: The first step in using a CNN for HAR is to pre-process the acceleration data. This typically involves segmenting the data into time windows of a fixed length and then normalizing the data so that it has zero mean and unit variance. These segments of data are then used as input to the CNN architecture.

CNN model construction: The CNN model has pooling, convolutional, and fully linked layers. Pooling layers reduce data dimensionality, whereas convolutional layers extract features from acceleration data. The retrieved features are utilised to classify activity in the fully linked layers.

The model is trained to identify patterns in the input data and extract those features in the convolutional layers. Convolutional layers produce a collection of feature maps through filters learned during training.

The pooling layers down-sample the feature maps to lower the data's dimensionality. The most common pooling processes are maximum pooling and average pooling, however there are more. With pooling, we may condense the feature maps without losing the most crucial details.

The fully connected layers are the last stage of the CNN model, and they are responsible for classifying the data based on the extracted characteristics. When the CNN model is run, it generates a probability distribution across the activities that shows how likely it is that each activity will be carried out.

Training the model: Once the CNN model is built, the next step is to train the model on labelled data. Labelled data is a dataset of acceleration data collected from a group of individuals performing a variety of activities. Using the labelled data, we can teach the model to identify the distinctive acceleration patterns that are characteristic of various actions.

Model parameters are tuned during training to get the best possible agreement between the model's predictions and the actual labels in the training data. Optimization algorithms like stochastic gradient descent and Adam are used to iteratively adjust the model's parameters in order to get the best possible fit for the data.

Evaluating the model: After training, the model must be assessed on a new dataset. This evaluation dataset measures the performance of the models on unseen data, estimating its performance on new data. Precision, accuracy, recall, and F1-score are the most frequent measures for HAR CNN models.

Thirty people, ranging in age from 18 to 60, contributed 11,771 samples (Micucci, Daniela, et al. 2017) representing a wide variety of human activities and falls. The samples are broken down into 17 fine-grained categories that are further categorised into two coarse-grained categories: those dealing with ADLs (activities of daily living) and those dealing with falls (falls).

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The four-layer CNN model is trained for five separate times, each time with a different batch size but with the same constant value of Lr = 0.0002 for all of the runs. In each iteration, the only variable that is altered is the batch size. For each of the five runs, the batch sizes are kept at 64, 128, 256, 522 and 32 respectively. The names of each run are automatically recorded and saved in the graph; the names of the runs are as follows:

1) Rural-frog-80

2) Comfy-bird-110

3) Smart-moon-101

4) Serene-firebrand-103

5) Northen-donkey-99

The batch size of Rural-frog-80 is 64, and the learning rate per iteration is 0.0002. The batch size of Comfy-bird-110 is 128 and its learning rate is 0.0002. The batch size of Smart-moon-10 is 256, and the learning rate is 0.0002. Serene-firebrand-103 has a batch size of 512 and a learning rate of 0.0002. Northen-donkey-99 has a batch size of 32 and a learning rate of 0.0002 per iteration. The system will choose all of the names for you automatically. When run, wandb involuntarily generates a new name for itself.

IV. Result and Discussions

As described in the methodology section, we ran the convolutional neural network with varying batch sizes, and the results of those experiments are discussed here.

Various measures, including precision, accuracy, recall, and F1-score, can be used to evaluate the performance of human activity detection systems utilising smartphone accelerometer data. These metrics quantify system performance and are used to evaluate systems.

Accuracy: Accuracy is the most basic and commonly used metric for evaluating the performance of a system. It measures the proportion of correctly classified instances over the total number of instances. Higher accuracy implies that the system is better at recognizing human activities.

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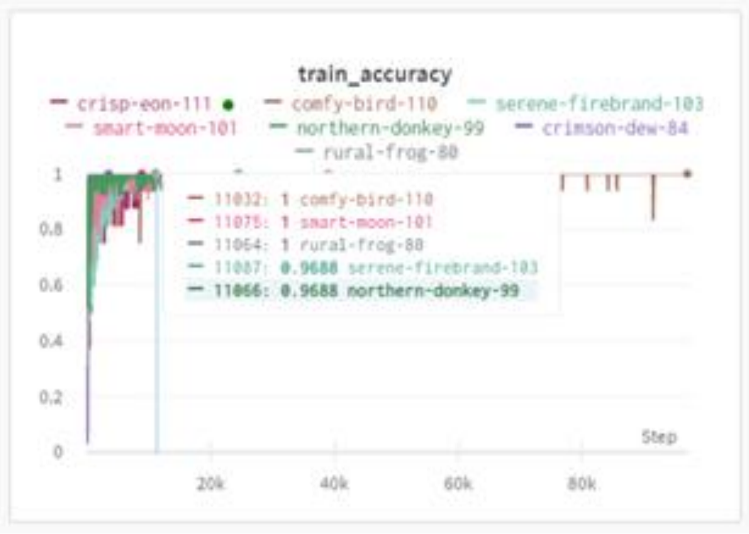

Figure 1 Training accuracy

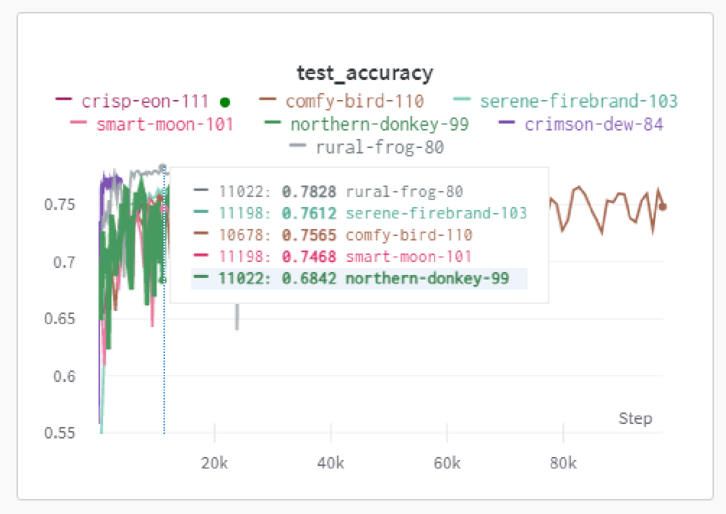

Figure 2 Test Accuracy

Recall: Recall measures the proportion of correctly recognized activities among all the activities present in the data. It reflects the ability of the system to identify all the relevant activities.

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Figure 3 Test Recall

F1-score: The F1-score is the harmonic mean of precision and recall and provides a balanced measure of the system's performance. It takes into account both the precision and recall, and a high F1-score indicates that the system has both high precision and high recall.

Figure 4 F1- Score

It is important to keep in mind that the performance of a system is dependent on the choice of activities to be recognized and the algorithms and models used for recognition. The performance of a system can also be impacted by various factors such as data quality, data variability, and computational resources. Therefore, it is necessary to use appropriate metrics and carefully evaluate the performance of the system in order to make informed decisions about the design and deployment of human activity recognition systems using smartphone accelerometer data.

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Form the 5 iterations and run it is found the test accuracy 78.28 as shown in the figure 2, which is the best among all other iteration. F1-score for the same is iteration(rural-frog-80) is found 77.91 which is best among all other as depicted in figure 4 of f1-score.

labels corresponding to the 17 classes are as 0 - 'StandingUpFS', 1 - 'StandingUpFL', 2 - 'Walking', 3 - 'Running', 4 - 'GoingUpS', 5 - 'Jumping', 6 - 'GoingDownS', 7 - 'LyingDownFS', 8 - 'SittingDown', 9 - 'FallingForw', 10 - 'FallingRight', 11 - 'FallingBack', 12 - 'HittingObstacle', 13 - 'FallingWithPS', 4 - 'FallingBackSC', 15 - 'Syncope', and 16 - 'FallingLeft'.

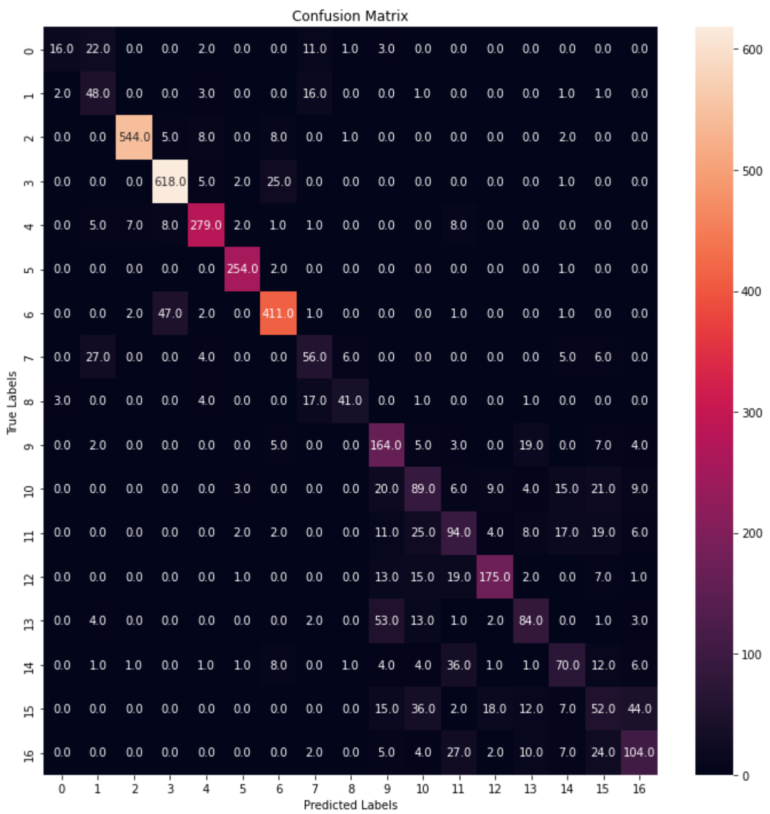

Figure 5 Confusion Matrix

Figure 5 shows a confusion matrix used to evaluate categorization systems. It displays a dataset's actual and anticipated class labels. Each class's TP, FP, TN, and FN are listed in the confusion matrix. A confusion matrix is a square matrix with rows reflecting real class labels and columns representing expected class labels. The matrix counts instances that were expected to belong to one class but really belong to another.

V. Conclusion

CNNs are robust to noise and variability in the data, which is a common problem in acceleration data. Using a CNN for human activity recognition using acceleration data from smartphones can be an effective approach as CNNs are able to learn features automatically and robust to noise and variability. In conclusion, using a custom CNN for Human Activity Recognition using acceleration data from smartphones can be an effective approach. One of the main advantages of using a CNN for HAR is its ability to learn features from the data automatically and its robustness to noise and variability in the data.

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