APPLICATION OF SMART WATCH-BASED DATA SET ANALYSIS IN MEDICAL INTERNET OF THINGS

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Abstract: In the field of medical physical therapy, the identification of human body activities is of great significance. Smartwatches are equipped with powerful sensors that provide a convenient platform for acquiring data sets to implement and deploy mobile motion-based behavioral biometrics. This study explores various activities of daily living and evaluates motion-based biometrics using smartwatches. The results show good results, indicating the applicability of these techniques in identifying human activities. And implemented through LSTM-CNN.

Keywords: medical physio therapy ,smart watches, sensors, biometric recognition, activity recognition, LSTM-CNN.

Introduction. Identifying and verifying an individual's physical condition and human body activities are crucial in the medical field. With advancing technology, smart watches have emerged as powerful tools in healthcare[1]. These watches combine intelligent sensors, data analysis, and real-time communication functions, offering new possibilities for medical monitoring and management.

Smart watches play a vital role in health monitoring by incorporating features such as heart rate sensors, exercise trackers, and sleep monitoring functions. These functions enable real-time monitoring of users' physiological indicators[2]. By collecting and analyzing this data, smart watches provide health status assessments and recommendations, facilitating better health management. Additionally, smart watches can monitor essential parameters like blood pressure and blood oxygen saturation, issuing early warnings and health risk alerts. The gyroscope sensor in smart watches accurately recognizes daily human activities, ensuring timely acquisition of important activity information.

Gyroscopes in smart watches also prove valuable for sports monitoring and fitness management[3]. By recognizing human body postures and movements, smart watches can accurately track activities like walking, running, and cycling. They record key indicators such as exercise duration, distance, and speed, offering personalized fitness suggestions. This benefits individuals seeking health management and sports enthusiasts, enhancing their understanding of exercise status and progress.

Furthermore, the activity recognition function of smart watch gyroscopes plays a significant role in chronic disease management and recovery. For instance, in stroke rehabilitation, smart watches can recognize hand movements and postures, monitor rehabilitation training progress and effectiveness, and provide real-time feedback and guidance. This personalized rehabilitation monitoring and auxiliary training improve patients' rehabilitation outcomes and quality of life. Smart watch gyroscopes can also identify and monitor various human activities, contributing to behavior analysis and management. By integrating activity recognition data with physiological parameters like heart rate and blood pressure, smart watches can provide more accurate health assessments and personalized treatment recommendations. The broad application prospects of smart watch gyroscopes in smart medical care offer accurate and personalized services for personal health. Further technological advancements will expand the application potential, introducing more innovation and convenience to smart medical care.

The study described in this article evaluates the use of accelerometer and gyroscope sensors on commercially available smart watches for biometric authentication and identification across a wide range of daily life activities. Different models are introduced for each activity. This study is unique as it assesses the biometric potential of smartwatches across numerous daily life activities. Assessing a diverse set of activities is crucial for generating effective data sets for medical human activity analysis.

Data Collection and Transformation. This section outlines the process of data collection and transformation. The study encompasses a variety of regular physical activities, most of which are performed daily. Physical activity is defined as specific identifiable actions with associated start and end times. While some activities (e.g., eating pasta) may not be practical for on-demand biometric systems, they are useful when subjects perform their normal daily activities. A continuous biometric system operating during normal activities proves valuable. However, activities like palming and writing are easily performed on demand. Section 6 discusses the overall biometric effectiveness of the campaign, considering its usefulness if executed on demand.The raw sensing data consists of time series sensor data stored in separate files. Each file contains data from one sensor (accelerometer or gyroscope) on one device (smartphone or smartwatch) for one subject. Therefore, there are four files associated with each subject, and the sensor data from these files can be linked through timestamp information collected during the same time period. Each sensor measurement is recorded on a separate line in the data file, following the format: subject-id (identifying the test subject), activity (code identifying the physical activity performed), timestamp (Unix time when the sensor value was recorded), x, y, and z values (sensor values for x, y, and z spatial axes). The format of recorded sensor data remains the same, regardless of whether it comes from an accelerometer or gyroscope on a smartphone or smartwatch. The accelerometer measures linear acceleration (in meters/second), while the gyroscope measures angular velocity (in rad/second). The raw sensor data used in this study is publicly available from the UCI repository as the WISDM Human Activity Recognition and Biometric Recognition Dataset[4]. Figure 1 illustrates a graphical representation of smartphone accelerometer data for walking and jogging activities, where the y-axis corresponds to the vertical direction and exhibits the largest magnitude. Jogging activities are more frequent than walking activities, as one would expect.

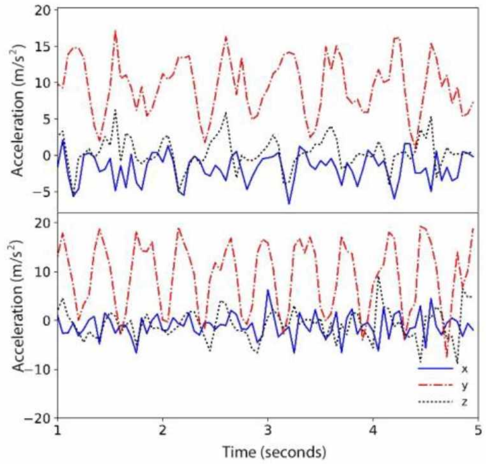
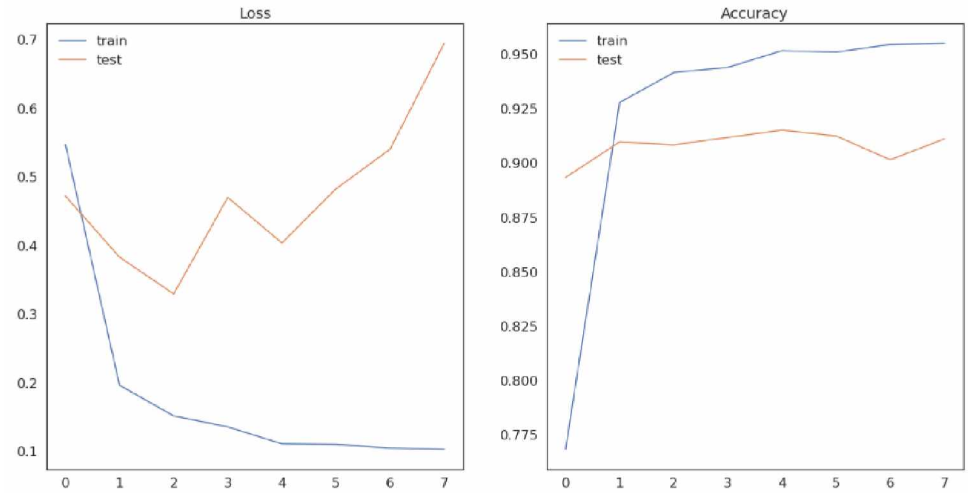


Figure 1 Plot of three-axis accelerometer data for smartphone walking activity (top) and jogging activity (bottom)

Classification algorithm. Three classification algorithms were used to generate the authentication and recognition models evaluated in the cost study: k-neighbors, decision trees, and random forests. We use implementations of these algorithms in Python's scikit-learn module, an open source library for data mining and analysis. Default parameters are used unless otherwise noted.

Evaluation process. In this study, a data set named "UCI_HAR_Dataset" was added and divided into a training set and a test set, where X_train and X_test contain two-dimensional tensors of the number of time steps (n_timesteps) and the number of features (n_features) , while y_train and y_test contain onedimensional tensors of the number of outputs (n_outputs). These parameters are used to build the model.

Model building. Define an LSTM model and use the model to run a complete pipeline, including data loading, model training, visualization results and other steps. Train the model on the training data using the



given model and grid search results, and evaluate the model performance on the test data. To get the best hyperparameters, get the best epochs and batches from the grid search results. The detection results obtained are shown in Figure 2.

Then build the CNN model and use adam as the optimizer. Find the loss rate and accuracy of the run. Finally, the CNN-LSTM neural network is constructed. After training the model, the loss rate and accuracy curves are constructed as shown in Figure 3. Three deep learning models are defined using different neural networks for training (LSTM, CNN, LSTM-CNN). Among them, the training process of each model includes techniques such as parameter optimization and early stopping to avoid overfitting.

Figure 2 Training data loss and accuracy

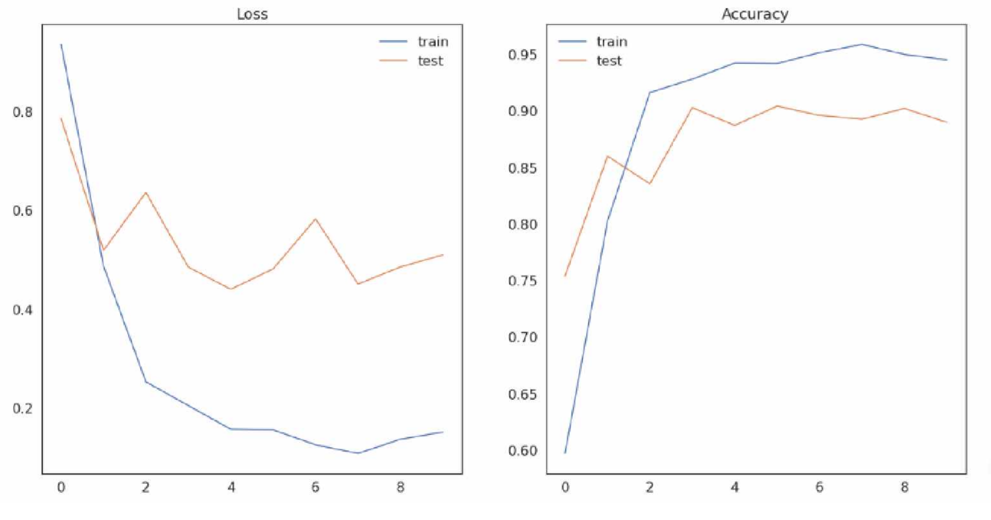


Figure 3 LSTM-CNN mode training data loss and accuracy

Conclusion. By analyzing the training results, we can clearly observe the ROC curve of the model, and the accuracy of the training results is still close to 100%. This study constructed a dataset for medical activity analysis by collecting and analyzing sensor data from smart watches. For the medical field, forming valid data sets is very important for accurate analysis and evaluation of human activities. Through smart watch data collection, we can obtain a large number of sample data of different activities, which provides strong support for medical activity analysis and research. From the overall research point of view,Human activity detection applications based on smart watches have broad application prospects in the medical field. The gyroscope sensor of smart watches can accurately identify and monitor human body activities, providing important support for smart medical care. With the continuous development of technology, smart watches will play an increasingly important role in medical monitoring, rehabilitation and health management, and provide more accurate and personalized services for personal health.

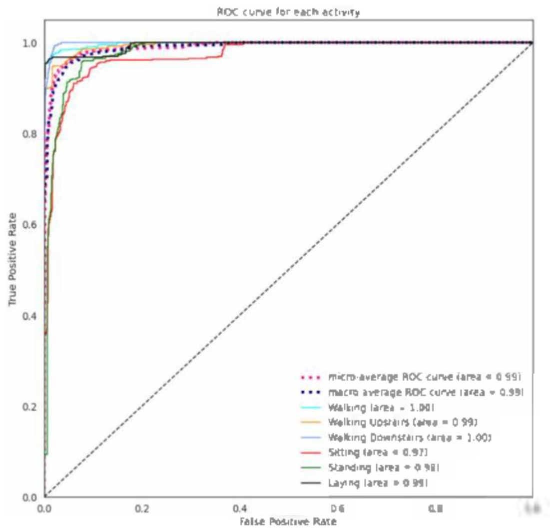


Figure 4 mode ROC curve for each activity

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