Predictive Activity Monitoring via Wearable Sensors

Introduction

The utilization of mobile devices and the incorporation of mobile health (mHealth) technologies have revolutionized how healthcare is accessed, managed, and delivered. Using the time-series sensor data collected through wearable devices, deep learning algorithms could be implemented to predict various human activities[1]. Our research question is whether we could predict the activity being performed by an individual based on the sequential data collected from wearable sensors over time. We also aimed to explore the best model using different data preprocessing choices, model designs, and hyperparameters. This research question is important because finding the best model for accurate activity prediction may help enhance healthcare monitoring, offer tailored interventions, and empower patient engagement.

Data Engineering Process

This dataset encompasses sequential sensor readings from nine subjects, containing activity labels and measurements from ankle and arm sensors in the x, y, and z axes[2]. The activity label denotes various activities, ranging from 0 for idle states to 12 for actions like front-back jumping. Notably, records associated with activity 0 were abundant, totaling 720,946, eclipsing counts for other activities, which had fewer than 28,000 entries each. Initially, we organized the data by subjects to ensure data from the same subject didn't overlap between training and validation sets. Then, we divided the dataset into an 80% training and 20% test set to explore model performance. In specific experiments, the training set was further split into validation and training subsets to fine-tune the best model parameters for testing on the test set. Subsequently, normalization was applied separately to numerical sensor columns in both training and validation sets to prevent data inconsistencies. Following this, sequences were generated for training and validation, maintaining the target activity for each sequence. A sequence length of 100 was chosen considering the sensor data's sampling rate of 50 Hz. We organized the data based on subjects and activities, creating sequences that tie each sequence exclusively to one subject and one activity. Our aim was to train the model to predict activities by understanding the sequence of data

Analysis

To better capture the long-range dependencies in the sequences, we utilized a long short-term memory (LSTM) model instead of traditional recurrent neural networks (RNN) because LSTM can capture and utilize information from earlier time steps in a sequence more effectively. We tried two different architectures.

Our initial model featured one LSTM layer and two fully connected (FC) layers, each with 256 hidden units. Dropout layers (0.5 and 0.2 rates) were inserted between the LSTM and FC layers to prevent overfitting. Using ReLU activation, the model made predictions based on class scores and was optimized using cross-entropy loss with the Adam optimizer. This model underwent 100 epochs with a batch size of 512, aiming for superior accuracy on both training and validation data. We considered two modifications to this model. First, we trained three separate models with different learning rates of 0.001, 0.01, and 0.05 to explore the effect of the learning rate on model performance. Then, we selected the best learning rate and applied L2 regularization with a lambda of 0.001. This regularization term was added to the loss computation to control the complexity of the model, discouraging the weights from becoming too large, which can lead to overfitting.

The second model involved two LSTM layers, four FC layers, and variable hidden unit sizes. The architecture included dropout layers (0.5 rate) after each LSTM layer, followed by FC layers that utilized batch normalization. Employing ReLU activation and the Adam optimizer, this model underwent 100 epochs with a batch size of 1024, aiming for superior accuracy on both training and validation data. We experimented with this network using two different variations of this dataset. Initially, we trained it on the complete dataset, and subsequently, we applied downsampling to the zero class while incorporating class weights to achieve a balanced dataset before training the model on this modified data.

Findings

We employed the LSTM model and tried three learning rates, including 0.001, 0.01, and 0.05. The resulting accuracy for the training set was the highest for a learning rate of 0.01 at the 100th epoch, approximating 88.83%. The training accuracy of a learning rate of 0.001 was 86.13% at the 100th epoch, with a more steady increase in accuracy. Conversely, the training accuracy with a learning rate of 0.05 showed the most fluctuations and did not appear to increase with epochs, approximating 72.30% at the 100th epoch. However, the accuracy on the validation set appeared to be similar across all three learning rates, showing no obvious increase in accuracy with more epochs and averaging around 73.50%. As a result, we opted for a learning rate of 0.001, which allowed the model to make more gradual adjustments. When L2 regularization was applied to the model trained with a learning rate of 0.001, the average training accuracy decreased compared to the model without L2 regularization. This was reasonable because the L2 regularization term aimed to reduce overfitting to the training data, consequently leading to a reduction in accuracy. However, the validation set accuracies for models with or without L2 regularization were similar. Because we observed an abundance of Activity 0 in the data set, we then applied the model with a learning rate of 0.001 and no L2 regularization to a separate training set without Activity 0. The resulting accuracy of the validation set without Activity 0 was significantly lower than that of the validation set with Activity 0, approximating 52.62% at the 100th epoch.

With the second architecture and a downsized dataset along with a 0.005 learning rate, the model remained unstable even after 100 epochs, failing to stabilize. It achieved a maximum validation accuracy of 15.38%, which translated to an 11% accuracy on the test set—indicating performance no better than random guessing, revealing the model's inability to learn. Subsequently, by training the model for 20 epochs with a reduced learning rate of 0.0005 and a batch size of 256, the accuracy improved to 72% on the validation set and 73.94% on the test set. However, the resulting confusion matrix revealed that the model predominantly predicted only the zero class, indicating inadequate learning.

Conclusion

In conclusion, our LSTM model demonstrated commendable accuracy in discerning various activities based on sequence data collected from wearable sensors. However, it predominantly excelled in predicting the majority class of zeros, highlighting the impact of imbalanced data. Despite attempting resampling techniques, the model struggled to capture patterns across other classes with high accuracy. Nevertheless, the confusion matrix showed some improvement. This emphasizes the importance of carefully choosing hyperparameters and developing robust strategies to address such class imbalances in the real-world healthcare application of activity prediction using wearable sensor data.

Individual Contribution: Each person contributed to the code, report, and presentation slides.

Code and Presentation

GitHub repository: https://github.com/Yutong-Lu/Datathon-5

Presentation slides: 12-CHL5230-F23

References

1. Athota RK, Sumathi D. Human activity recognition based on hybrid learning algorithm for wearable sensor data. Measurement: Sensors. 2022 Dec 1;24:100512.
2. HIVE Lab. mHealth and Machine Learning [dataset]. 2023 Fall [cited 2023 Nov 19]. University of Toronto.