The effect of recentness of consumer-grade wearable training data on the ability of a Deep Neural Network to identify users

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1. Introduction

- Consumer-grade wearable devices such as smart watches and heart rate monitors are becoming increasingly popular, accessible and accurate when collecting data.
- This data can give away information about users such as general fitness and behaviour patterns, which can be useful for medical practitioners to help patients, sports teams for improving training and elderly care for monitoring patients [1].
- Patterns in data that are collected from these wearables, such as resting heart rate, change over time [2]. This means that time-series training data could potentially become outdated.
- Therefore any model using this data to identify users on future unseen test data, might perform worse when trained on windows of data that are less recent. This included the Deep Neural Network (DNN).

2. Research Question

How does the recentness of consumer-grade wearable data used for training a Deep Neural Network (DNN), impact the ability of the model to identify users?

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3. Method

- The DNN model which is used in this study is a combination of the convolutional neural network (CNN), and the long-short term memory layer (LSTM). This is called a CNN-LSTM model.
- Three experiments were conducted:
  - The sliding window experiment, which is shown in figure 1. The recentness is changed by using different subsets of data for all users.
  - The per person sliding window experiment, which has a similar setup as in figure 1. The difference is that the recentness of training data was only changed for one user.
  - The expanding window experiment, which is shown in figure 2. The recentness was changed by removing the oldest available training windows for all users.

Figure 1: Simplified version of the sliding window experiment

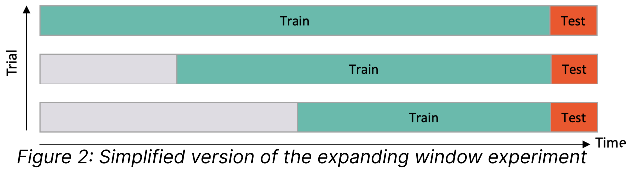

Figure 2: Simplified version of the expanding window experiment

4. Results

- Figure 3 shows that the DNN model performed better on more recent training data. It performed worse on data where there was a gap of approximately 157 days between training and test sets.
- The results from figure 4 show that increasing the recentness for a single user improves the ability of the model to identify that specific user. However, it does not necessarily improve the ability to identify every user.
- The graph in figure 5 show that the model performs better when there is more data.

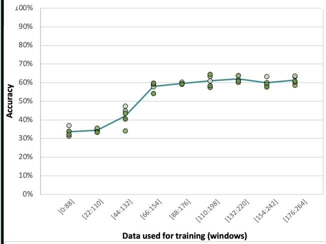

Figure 3: Results of the sliding window experiment. Test set = [264:330]

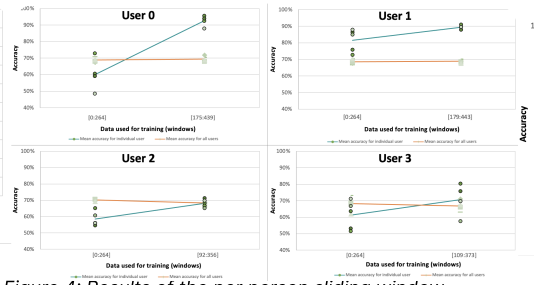

Figure 4: Results of the per person sliding window experiment. Each graph represents a seperate experiment.

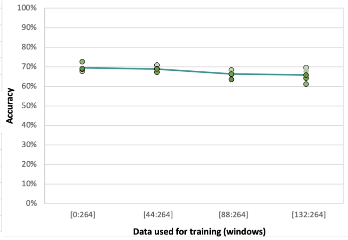

Figure 5: Results of the expanding window experiment. Test set = [264:330]

5. Conclusion

- The model performs better when trained on newer training data. The decrease in performance was very sudden.
- No subset of training data used by the model was found to perform better than training on all available training data. Therefore the amount of training data is more important in this setup than the recentness of the data.
- The decrease in performance when removing the oldest training data was small. Therefore, if training speeds are important, training on the most recent data is a good alternative.
- Only increasing recentness for a single user is beneficial for that user, since the model identifies their data with a larger accuracy. It is however not always beneficial for every user.

6. Limitations

- The availability of data was a limitation. For every user there was less than 500 days of data, for some there was as little as 150. However, heart rate pattern changes will most likely change more across multiple years.
- Another limitation was data reliability. There are missing heart rate and step count values, which could impact the performance of the model.

7. References

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[2] Reimers, A. K., Knapp, G., Reimers, C. D. (2018). *Effects of Exercise on the Resting Heart Rate: A Systematic Review and Meta-Analysis of Interventional Studies.* Journal of clinical medicine, 7(12), 503. https://doi.org/10.3390/jcm7120503