USING ACCELEROMETRIC AND GYROSCOPIC DATA TO IMPROVE BLOOD PRESSURE PREDICTION FROM PULSE TRANSIT TIME USING RECURRENT NEURAL NETWORK

Shrimanti Ghosh[1], Ankur Banerjee[2], Nilanjan Ray[1], Peter W Wood[2], Pierre Boulanger[1], Raj Padwal[2]

[1] *Department Of Computing Science, University Of Alberta, Edmonton, Alberta, Canada*

[2] *Department Of Medicine, University Of Alberta, Edmonton, Alberta, Canada*

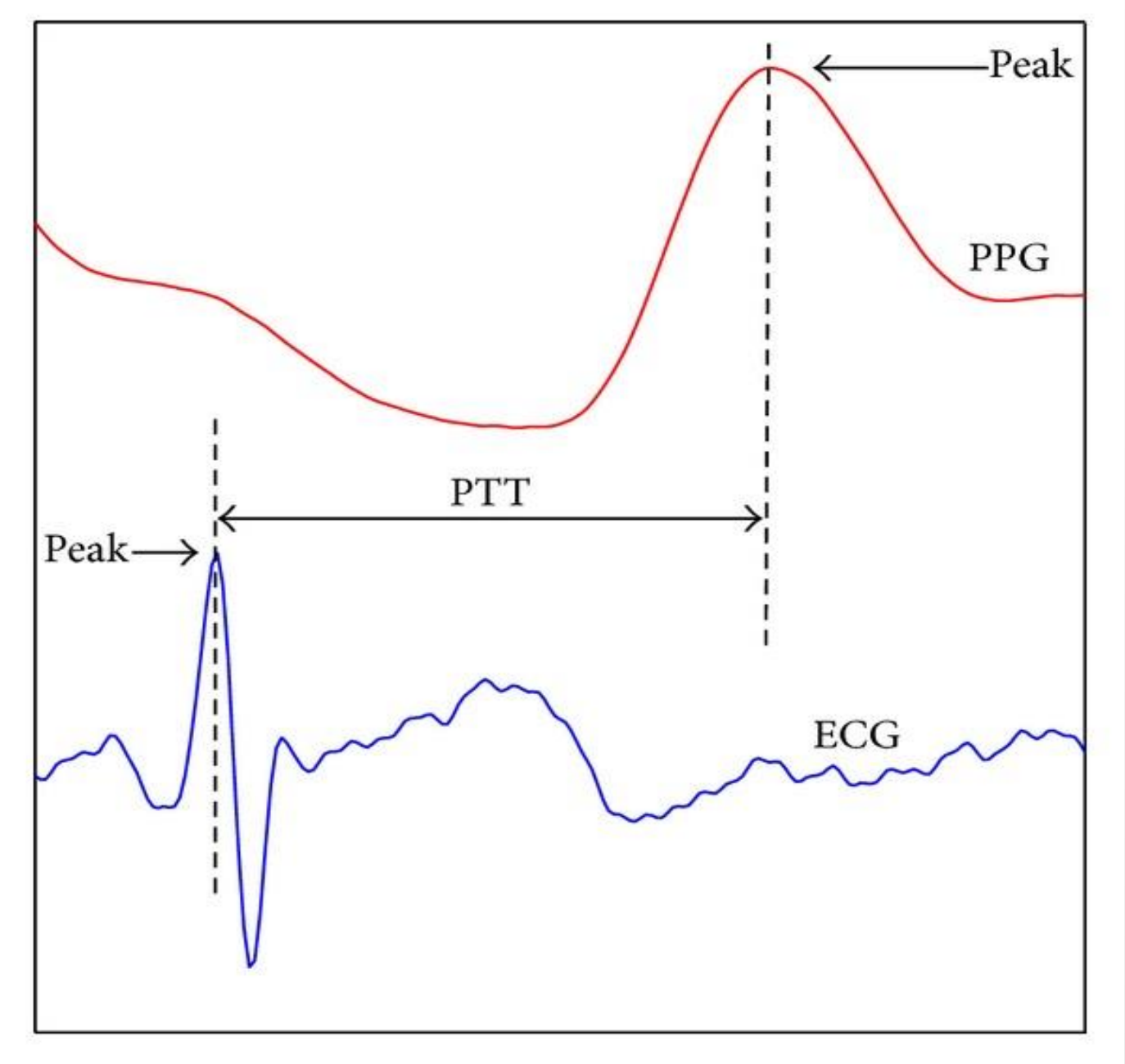
E-mail: shrimant@ualberta.ca **LinkedIn:** https://ca.linkedin.com/in/shrimanti-ghosh-1931a0129

Introduction

- Current methods of measuring and monitoring **blood pressure (BP)** require either invasive procedures or intermittent inflation of a cuff to restrict blood flow, which can be cumbersome and cause discomfort.
- A reliable, accurate non-invasive and continuous BP monitoring is highly useful.
- Pulse Transit Time (PTT) has the potential to estimate BP in a continuous fashion [1].

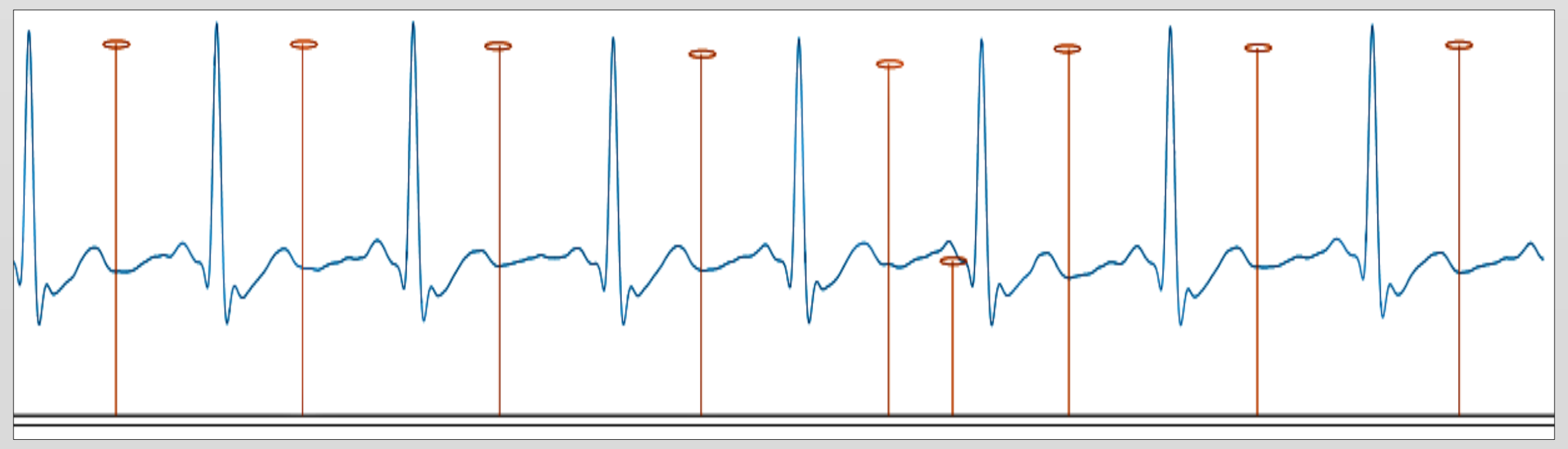
Pulse Transit Time (PTT)

- PTT can be defined as the time between the R-peak of an ECG signal and the peak of the PPG signal when measured within the same cardiac cycle shown in the figure below.



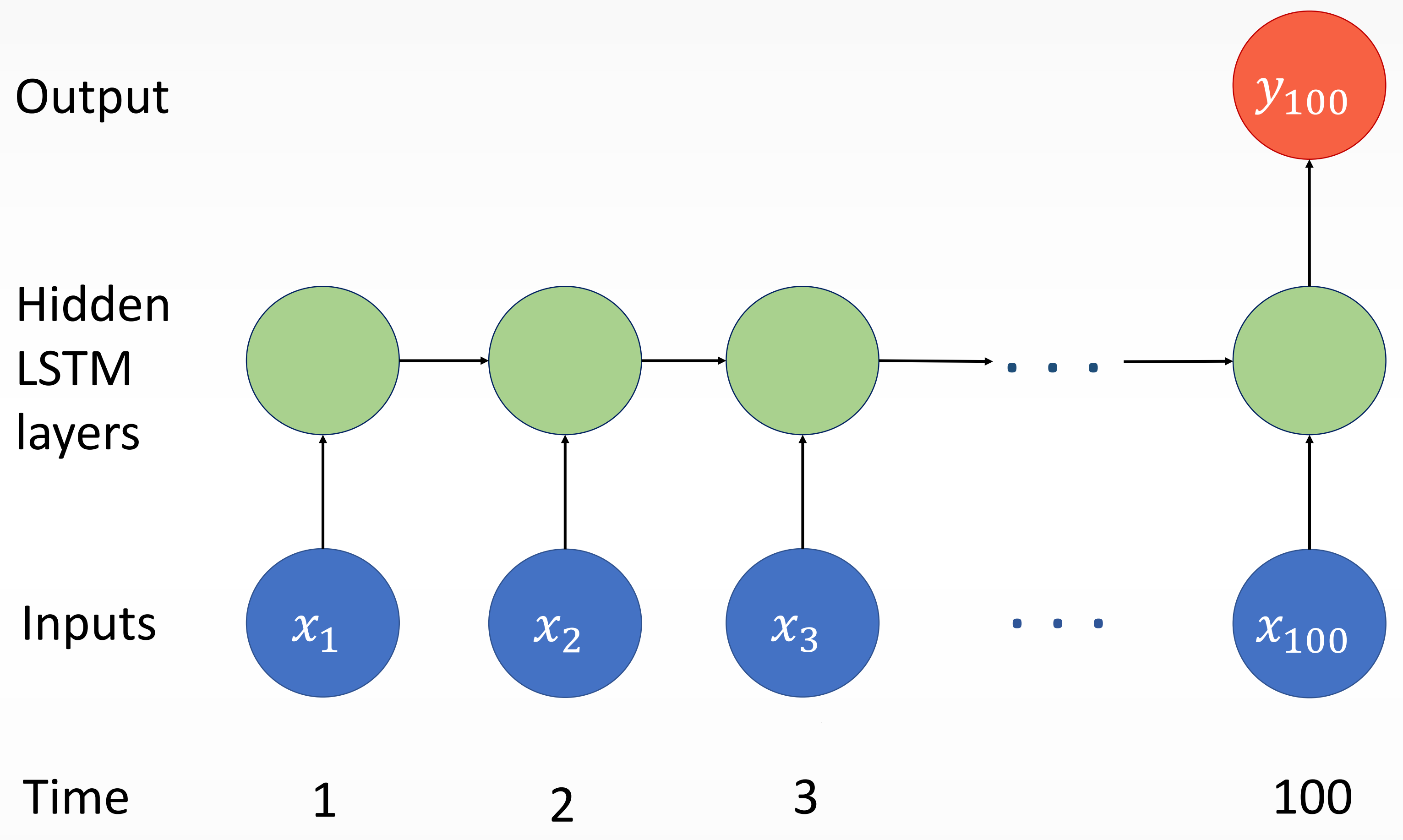
Automated PTT Calculation

Automated pulse transit time was computed using windowed *cross-correlation* between ECG and sparsified PPG signals [2].



ECG Signal (blue) and sparsified PPG Signal (red)

RNN (LSTM) Model



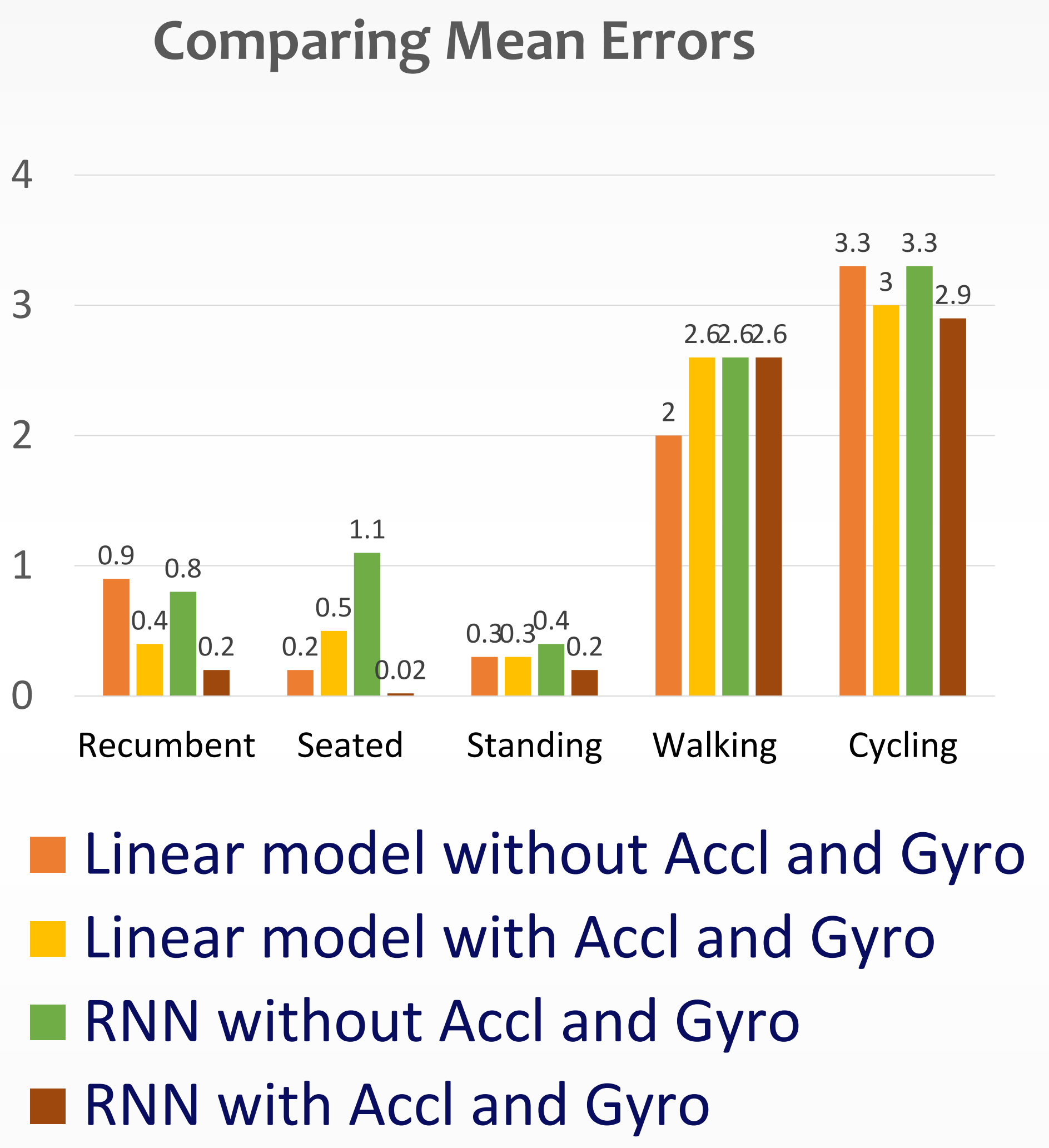
- Input x_i = **[ECG, PPG, PTT, $\mathbf{Accl_{x,y,z}}$, $\mathbf{Gyro_{x,y,z}}$]**, is a vector of 9 elements and Output y_i = **BP value**, is a scalar.
- During training 100 samples are fed to the LSTM and the network outputs 100th BP value in the sequence [3].

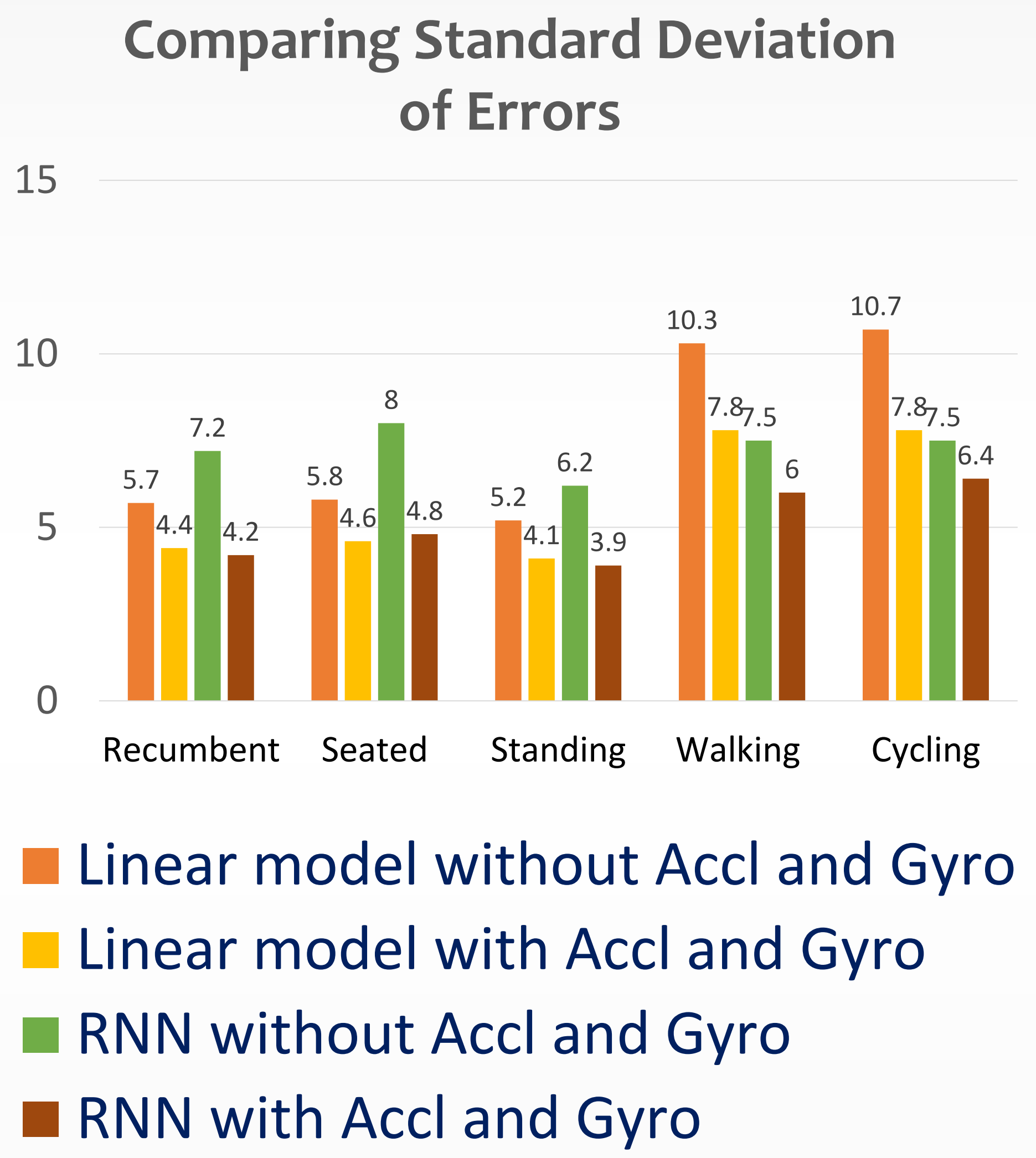
LSTM Model (many-to-one)

- 32 neurons in first hidden layer.
- Dropout layer to prevent overfitting.
- 1 neuron in the output layer.

- Training was performed with 50 epochs and batch size 64.
- Implemented using Keras API [4] with TensorFlow and on a double NVIDIA GeForce GTX 1080.

Results





Maximum permissible Mean ± Standard Deviation is **5 ± 8**
(Lower the value ⟹ more accurate prediction)

Conclusion

- A large-scale study was performed involving 50 healthy volunteers.
- Accl and Gyro values improved continuous BP prediction in motionless condition as well as during motion using RNN.
- The training set contained data collected in motionless condition while, in the test set we had data in presence of motion as well. RNN also predicted the new data quite well (handles the *Extrapolation problem*).

References

1. H. Gesche et al., “Continuous blood pressure measurement by using the pulse transit time: comparison to a cuff-based method”, Springer-Verlag 2011.
2. S. Ghosh, et.al. “Continuous Blood Pressure Prediction from Pulse Transit Time Using ECG and PPG Signals”, HI-POCT, 2016.
3. Peng Su, et.al. “Learning to Predict Blood Pressure with Deep Bidirectional LSTM Network”, CoRR 2017.
4. Chollet, Francois et.al. “Keras”, published by GitHub, 2015.