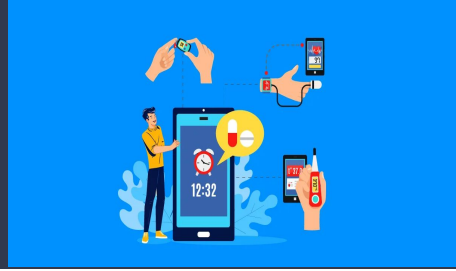
Machine Learning Prediction in mHealth Data

Team 15: Xiaoxuan Han, Hunter Ponzzebon, Gwen Eagle

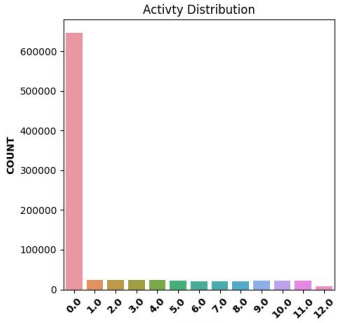


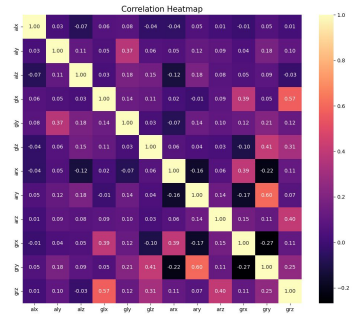
Introduction:

- **Dataset:**
  - mHealth data (999,999 records, 14 variables);
  - Time-series data on linear and angular motion on the x-,y-,z-axis during *13 different activities*
- **Goal:** To build a machine learning model that can accurately ascertain activity type based on multidimensional time series data
  - Recurrent Neural Network (RNN)
  - Long Short-Term Memory Neural Network (LSTMNN)

Data Engineering & EDA :

- **Data Engineering:**
  - Data split into 80% for training and 20% for test;
  - Data normalization;
  - Addressed class imbalance: undersampled *class 0* and oversampled *class 12;*
  - Sequence generation
- **EDA:**
  - No missing data;
  - Correlation heatmap on *12 sensors*



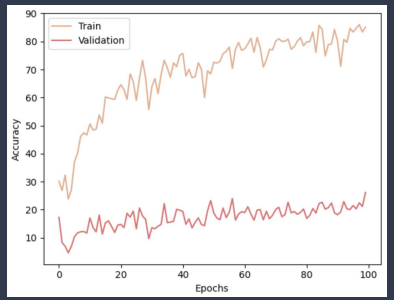


Model Comparisons

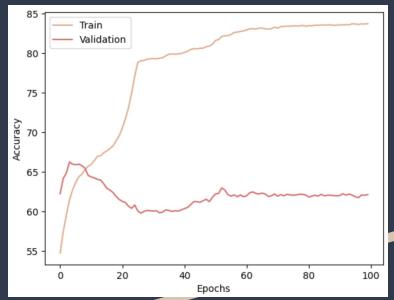
Features: 12 motions (linear and angular motion on the x-,y-,z-axis)
Target: Activity (multi-classes vs. binary classes)

RNN:

- 256 hidden units, 100 epochs, learning rate = 0.001/0.00001, batch size = 512, regularization term = 0.0001/0.00001



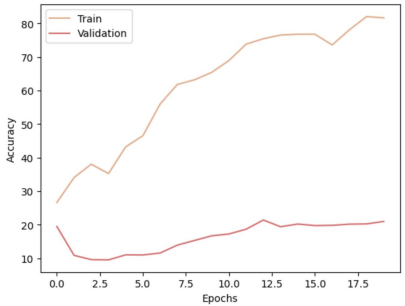
Multi-class (13 classes)



Binary class

LSTMNN:

- 256 hidden units, 20 epochs, learning rate = 0.001/0.00001, a batch size = 512, regularization term = 0.0001/0.00001



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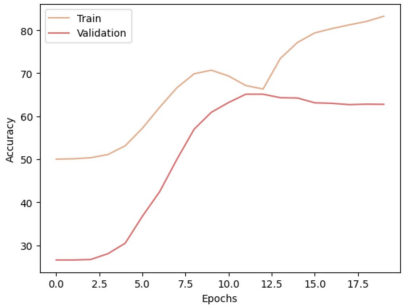

Binary class

Findings: The RNN and LSTMNN model for the activity type performed similarly (validation accuracy of ~20%); the RNN and LSTMNN model for the presence of activity performed similarly (validation accuracy of ~62%).
Limitations: A high degree of overfitting might have occurred in both models, potentially due to the models trying to predict a high number of classes based on a low number of subjects, as well as a high degree of class imbalance.