HUMAN ACTIVITY RECOGNITION

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1. Input Pipeline

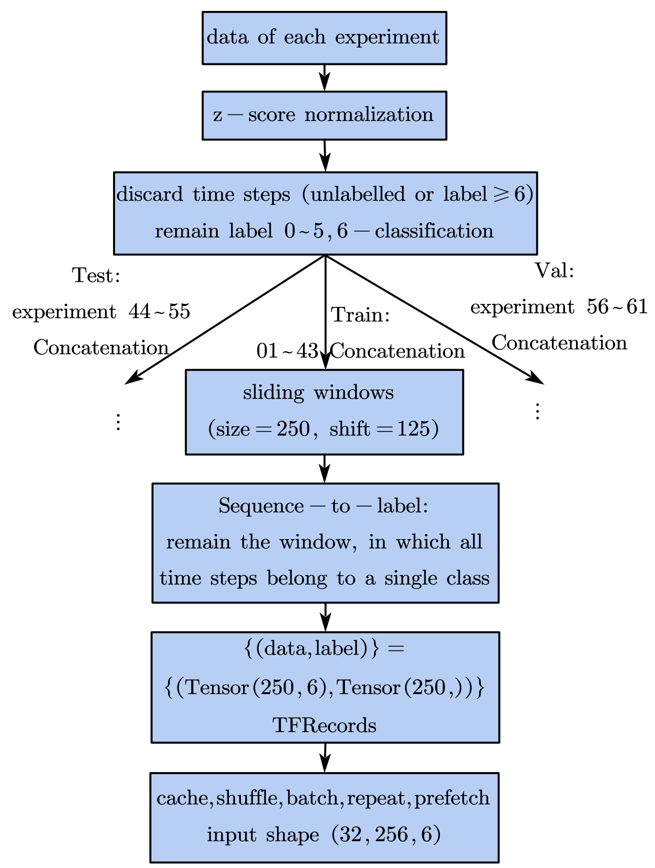

Abbildung 1: *Input Pipeline*

2. Model

- Selection of classification tasks
  - Sequence-to-Label (S2L) classification tasks
- LSTM
  - LSTM blocks: which include one LSTM layer, one BN layer to avoid overfitting, and use tanh as the activation function
  - Each LSTM Block returns a sequence result
  - Dropout layer
  - Pooling layer and dense layer to get a certain label
- GRU
  - GRU blocks: which include one GRU layer, one BN layer to avoid overfitting, and use tanh as the activation function
  - Each GRU Block returns a sequence result
  - Dropout layer
  - Pooling layer and dense layer to get a certain label

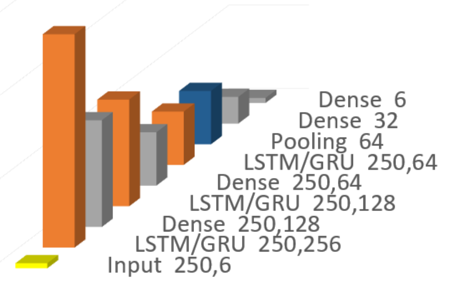

Abbildung 2: *Model architecture*

3. Training and hyperparameter optimization

- Training
  - Loss function: sparse categorical cross entropy
  - Optimizer: Adam
- Hyperparameter optimization
  - Hyperparameter tuning for LSTM
  - Hyperparameter tuning for GRU

Trial	1	2
Block type	GRU	LSTM
Pooling type	GlobalMax	GlobalMax
Total steps	7500	4000
Learning rate	6.58e-5	5.40e-5
Dropout rate	0.44	0.31
Val accuracy	94.05%	93.83%

Table 1: Some results of hyperparameter tuning

4. Evaluation and Visualization

- Feed the sliding windows without overlap into the model
- The predict part is thinner than the ground truth
- The prediction fits well with the ground truth

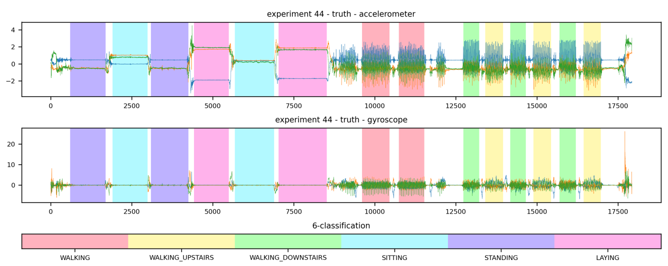

Abbildung 3: *Ground Truth*

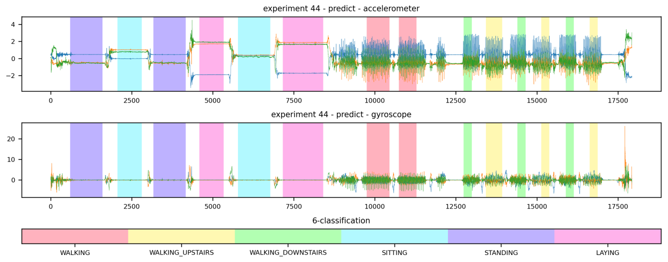

Abbildung 4: *Prediction*

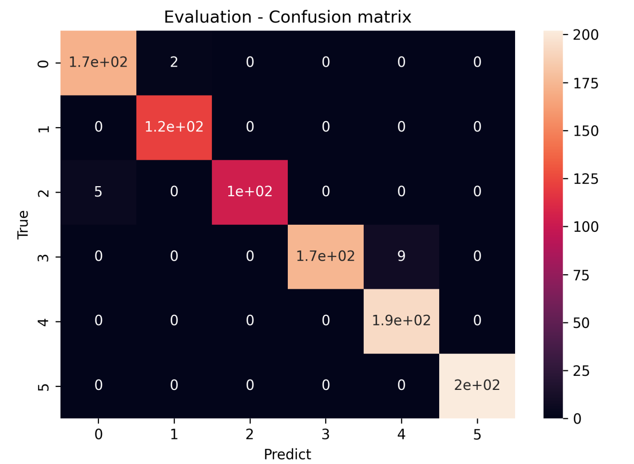

Abbildung 5: *Confusion Matrix*

5. Conclusions

- At the end, we choose GRU model, we can see that the prediction fits well with the ground truth

Model	Test accuracy
GRU	98.3%

Table 2: Final result

- The original dataset is highly imbalanced. After we drop out the data of postural transitions, we can get a good result of the human activity recognition task