* I have put the structure of the input data into a 3d array instead of a 4d array (similar to our previous paper); number of traials \* number of axis and sensors \*number of steps so:

21787\*24\*101. On the matlab data it was structured this way:

Axis (x,y,z) 8 sensors number of trials \* number of steps , the three axes were merged together with all sensors to have 24 in order to get 24 \* 21787 \* 101 and then it was restructured to the final shape 21787\*24\*101.

Data was split into 75/25 and then the below models were used and results were as follow:

Th baseline model architecture is given below:

Table 1 Baseline architecture

|  |  |  |
| --- | --- | --- |
| Layer Name, Kernel Size | Stride/ Padding | Activation Function |
| Input data |  |  |
| block1\_conv1 (Conv2D), 64 [3×3] | 1/valid | Relu |
| block1\_conv2 (Conv2D), 128 [3×3] | 1/valid | Relu |
| block1\_pool (MaxPooling2D), [2×2] | 2 |  |
| flatten (Flatten) |  |  |
| dense\_1 (Dense) 512 |  | Relu |
| dropout (Dropout), Rate = 0.1 |  |  |
| dense\_2 (Dense) 256 |  | Relu |
| dense\_3 (Dense) 128 |  | Relu |
| dense\_4 (Dense) |  | Linear |

The architectures used are: InceptionTimePlus, XCM [1], RNNplus (Conv1d + Stacked LSTM architecture), multilevel Wavelet Decomposition Network (mWDN) [2], and Time Series Transformer plus(TSTPlus)[3].

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Model | Outcome | train\_loss | valid\_loss | mae | \_rmse | time |
| InceptionTimePlus | hip\_flexion\_moment | 0.011134 | 0.012069 | 0.079863 | 0.109861 | 00:03 |
| hip\_adduction\_moment | 0.003153 | 0.004647 | 0.04867 | 0.068172 | 00:03 |
| knee\_moment | 0.006261 | 0.009275 | 0.065505 | 0.096307 | 00:03 |
| ankle\_moment | 0.006588 | 0.008992 | 0.064301 | 0.094826 | 00:03 |
| subtalar\_moment | 0.002926 | 0.003238 | 0.042287 | 0.056899 | 00:03 |
|  |  |  |  |  |  |  |
| XCM | hip\_flexion\_moment | 0.005935 | 0.006687 | 0.057467 | 0.081776 | 00:03 |
| hip\_adduction\_moment | 0.003965 | 0.004625 | 0.048622 | 0.06801 | 00:03 |
| knee\_moment | 0.005244 | 0.006825 | 0.054552 | 0.082616 | 00:03 |
| ankle\_moment | 0.005927 | 0.006976 | 0.054358 | 0.083525 | 00:03 |
| subtalar\_moment | 0.001422 | 0.001554 | 0.026351 | 0.039424 | 00:03 |
|  |  |  |  |  |  |  |
| RNNplus | hip\_flexion\_moment | 0.010052 | 0.010684 | 0.073293 | 0.103365 | 00:01 |
| hip\_adduction\_moment | 0.007339 | 0.008128 | 0.066246 | 0.090155 | 00:01 |
| knee\_moment | 0.01064 | 0.011547 | 0.072723 | 0.107456 | 00:01 |
| ankle\_moment | 0.010795 | 0.011607 | 0.072666 | 0.107734 | 00:00 |
| subtalar\_moment | 0.002914 | 0.003292 | 0.042558 | 0.057378 | 00:01 |
|  |  |  |  |  |  |  |
| mWDN | hip\_flexion\_moment | 0.003504 | 0.00482 | 0.048505 | 0.069426 | 00:04 |
| hip\_adduction\_moment | 0.002896 | 0.003829 | 0.044089 | 0.061877 | 00:04 |
| knee\_moment | 0.003108 | 0.004797 | 0.045377 | 0.06926 | 00:04 |
| ankle\_moment | 0.003252 | 0.004849 | 0.043914 | 0.069638 | 00:04 |
| subtalar\_moment | 0.000882 | 0.001045 | 0.021213 | 0.032323 | 00:04 |
|  |  |  |  |  |  |  |
| TSTPlus | hip\_flexion\_moment | 0.009211 | 0.009598 | 0.068577 | 0.097972 | 00:03 |
| hip\_adduction\_moment | 0.009311 | 0.00919 | 0.069232 | 0.095863 | 00:03 |
| knee\_moment | 0.014021 | 0.01431 | 0.079547 | 0.119626 | 00:03 |
| ankle\_moment | 0.010111 | 0.010767 | 0.068799 | 0.103762 | 00:03 |
| subtalar\_moment | 0.002593 | 0.002829 | 0.038476 | 0.053188 | 00:03 |
|  |  |  |  |  |  |  |
| basline model | hip\_flexion\_moment | 0.0077 | 0.0077 | 0.0627 | 0.077 | 00:07 |
| hip\_adduction\_moment | 0.0082 | 0.0074 | 0.0628 | 0.074 | 00:07 |
| knee\_moment | 0.0071 | 0.0073 | 0.0574 | 0.073 | 00:07 |
| ankle\_moment | 0.0092 | 0.0082 | 0.0569 | 0.082 | 00:07 |
| subtalar\_moment | 0.0011 | 0.0011 | 0.021 | 0.011 | 00:07 |

[1] Fauvel, Kevin, et al. "XCM: An Explainable Convolutional Neural Network for Multivariate Time Series Classification." *Mathematics* 9.23 (2021): 3137.

[2]Wang, Jingyuan, et al. "Multilevel wavelet decomposition network for interpretable time series analysis." *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. 2018.

[3] George Zerveas et al. A Transformer-based Framework for Multivariate Time Series Representation Learning, in Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery and Data Mining (KDD '21), August 14--18, 2021. ArXiV version: https://arxiv.org/abs/2010.02803