We study handwritten symbols (isolated characters, digits, gestures, and signatures) produced by humans and machines, and compare and contrast several deep learning models. We find that if symbols are presented as static images, they can fool state-of-the-art classifiers (near 75% accuracy in the best case) but can be distinguished with remarkable accuracy if they are presented as temporal sequences (95% accuracy in the average case). We conclude that an additional layer of security to keep attackers at bay...

**A. MODELS PERFORMANCE**

The performance of all the RNNs over all our evaluated datasets. The model is fine-tuned on 20% of the training data.

**C. GRU ROBUSTNESS**

We train our GRU on different splits of the original datasets.

**D. EFFECT OF INPUT DEVICE**

SN-MMG dataset contains stylus and finger input data. Train: A single type of data, stylus or finger. Test: With both types of input data.

Velocity profile examples from our evaluated datasets, describing how a handwriting movement "unfolds" over time. A moving average filter of size 3 is applied to remove artificial jitter introduced by the input device. For each handwriting movement, a synthetic version is generated with the U.S. model and plotted together with their human counterparts.

Synthetic and human samples are visually similar but the synthetic velocity profiles are smoother than their human counterparts.

We include the Table 1: FLOPS Memory, showing the number of trainable model parameters and the memory footprint.

**REFERENCES**