Supplementary Materials for

Video-based Formative and Summative Assessment of Surgical Tasks using Deep Learning

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Supplementary Information

Hyperparameter Selection. During training the Mask R-CNN, the learning rate is initiated as 0.001, and the weight decay and momentum are 0.0003 and 0.9, respectively. The learning rate decreased by a factor of ten after the 20th epoch.

To extract salient features from motion sequences via the DAE, binary cross-entropy is minimized with a learning rate of 0.001. On the other hand, the classifier is trained with a mean squared error loss function when predicting the FLS scores and cosine similarity when performing classification, as it is shown to provide superior results on datasets with a limited sample size when trained from scratch[1]. The learning rate is 0.0002. Further, an Adam optimizer is used when training the model. Finally, the Scaled Exponential Linear Unit (SELU)[2] activation function is used for all the convolutional layers unless stated otherwise in Fig. S4. Finally, L2 regularizing (0.00001) is applied as both the kernel and activity regularizer[2].

Supplementary Figures

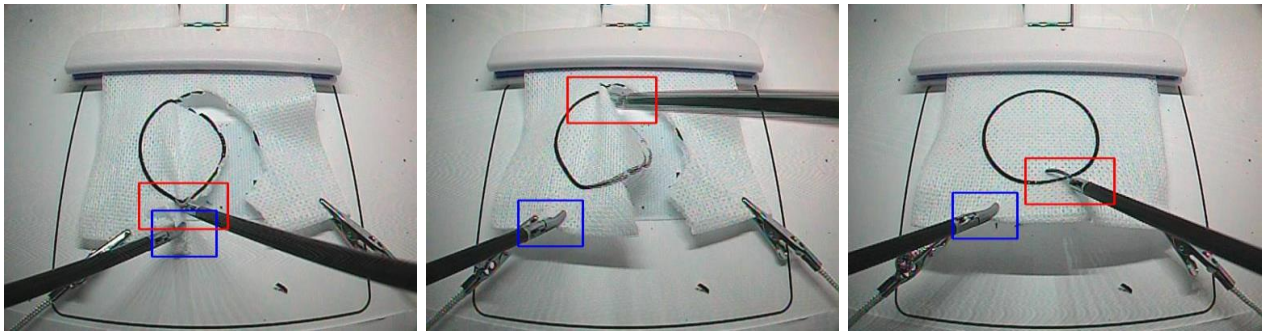
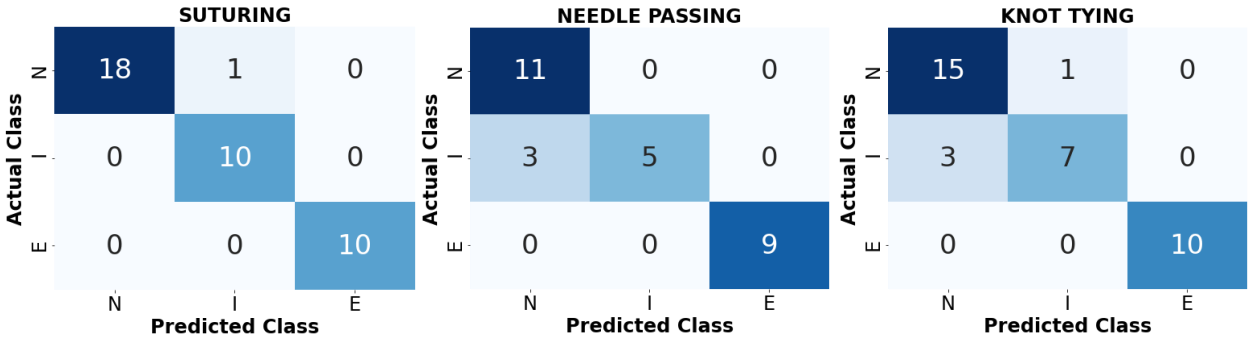
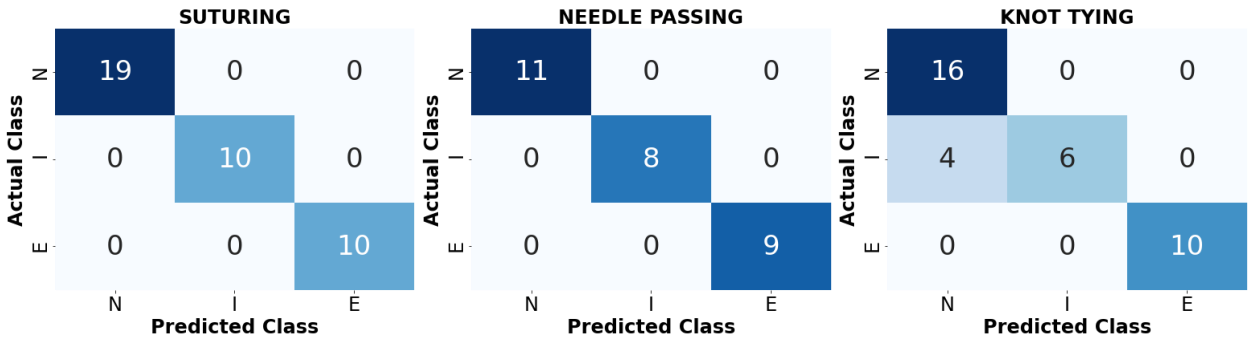


Fig. S1. Mask R-CNN output. Sample regressed bounding boxes of the tools. It is observed that the Mask R-CNN can successfully locate the tools when there is an intersection (left), blurry image (middle), and different tool angles (right).



(a)



(b)

Fig. S2. Confusion matrices for surgical datasets. (a) For the JIGSAWS dataset via the LOUO CV scheme. Here, N, I, and E stand for Novice, Intermediate, and Expert, respectively. **(b)** For the JIGSAWS dataset via the LOSO CV scheme.

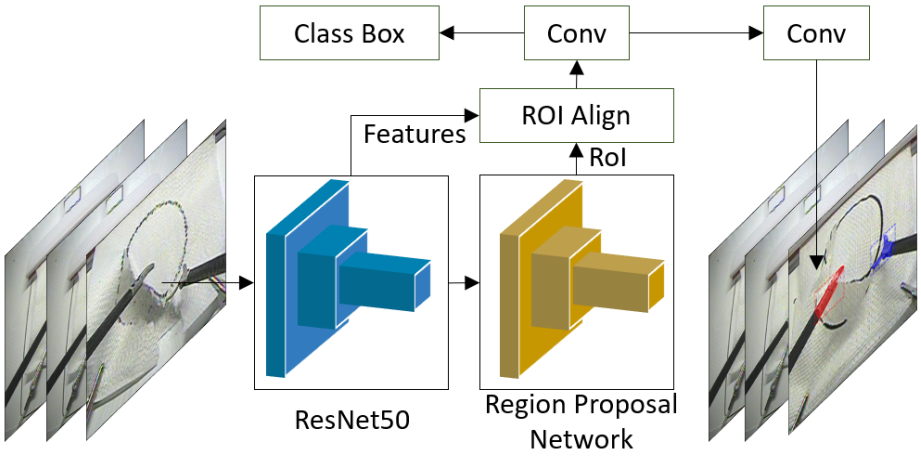


Fig. S3. Mask R-CNN architecture. It consists of a CNN-backbone, ResNet50, and Region Proposal Network (RPN) to output object properties.

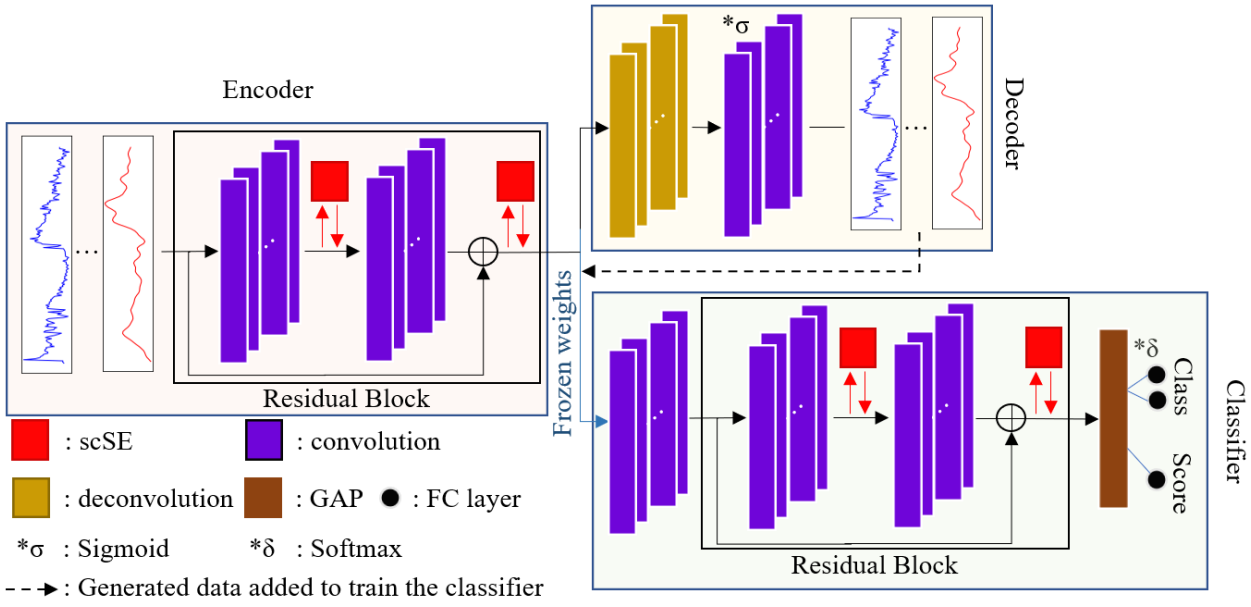


Fig. S4. The DAE and classifier structure. The figure illustrates the encoder, decoder, and classifier in their utilized order.

Supplementary Tables

Table S1. FLS score statistics based on binary classes for the PC datasets.

Dataset		No. of samples	Mean Duration (sec)	STD Duration (sec)	Mean FLS score	STD FLS score
Main	**Pass**	1842	73.5	25.0	208.3	24.3
	Fail	213	161.9	36.9	115.3	33.7
	Overall	2,055	82.7	37.8	198.7	38.1
Additional	**Pass**	202	86.0	23.4	185.2	19.3
	Fail	105	148.5	33.0	121.8	31.0
	Overall	307	107.4	40.2	163.5	38.5

Table S2. Breakdown of Spearman correlation coefficients, ρs, for OSATS scores prediction via the LOUO CV.

Task	Respect for tissue	Suture/needle handling	Time and motion	Flow of operation	Overall performance	Quality of final product
ST	0.25[ʔ]	0.67	0.66	0.59	0.53	0.43
NP	0.69	0.70	0.89	0.76	0.72	0.68
KT	0.75	0.78	0.86	0.78	0.76	0.87

[ʔ] $p > 0.05$. ST: suturing, NP: needle passing, KT: knot tying.

Table S3. Classification scores (<0.97) for LOSO CV and other CV schemes.

Author	Method	Suturing	Needle Passing	Knot Tying	Mean
Lajko *et al.*[3] [2021]	CNN	0.807	0.797	0.804	0.803
Anh *et al.*[4] [2020]	Autoencoder	0.835	0.823	0.806	0.821
Lajko *et al.*[3] [2021]	CNN + LSTM	0.816	0.832	0.828	0.825
Lajko *et al.*[3] [2021]	ResNet	0.819	0.842	0.835	0.832
Anh *et al.*[4] [2020]	LSTM	0.951	0.915	0.896	0.921
Wang and Fey[5] [2018]	CNN	0.925	0.954	0.913	0.931
Anh *et al.*[4] [2020]	CNN-LSTM	0.964	0.934	0.910	0.936
Anh *et al.*[4] [2020]	LSTM	0.965	0.941	0.912	0.940
Soleymani *et al.*[6] [2021]	CNN + FFT (4-fold)	N/A	N/A	N/A	0.942
Anh *et al.*[4] [2020]	CNN	0.968	0.954	0.927	0.950
Wang and Fey[7] [2018]	CNN-GRU	N/A	N/A	N/A	0.960
VBA-Net	***DAE + Classifier***	***1.0***	***1.0***	***0.926***	***0.975***

DAE: Denoising autoencoder, FFT: Fast Fourier Transform, HMM: Hidden Markov Model

Table S4. Breakdown of Spearman correlation coefficients, ρs, for OSATS score prediction via the LOSO CV.

Task	Respect for tissue	Suture/needle handling	Time and motion	Flow of operation	Overall performance	Quality of final product
ST	0.51	0.63	0.64	0.57	0.58	0.68
NP	0.52	0.77	0.65	0.69	0.55	0.43
KT	0.68	0.65	0.76	0.59	0.80	0.64

ST: suturing, NP: needle passing, KT: knot tying.

References

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