From the DESK (Dexterous Surgical Skill) to the Battlefield - A Robotics Exploratory Study

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Learning Objectives

- Identify the challenges involved in deploying a variety of surgical robots in the battlefield.
- Discuss how knowledge gained from the simulation environment can be leveraged to accelerate learning in deployable robots with different kinematic chains.
- Understand the relationship between surgical gestures and robotics performance using common machine learning methods.

Background and Motivation

Future battlefield medical operations call for robotic systems that can provide patient care at the point of injury. Autonomous behavior in such systems is key for situations of limited bandwidth, latency, and loss-of-signal. Skills learned in controlled scenarios, where data is abundant, should be transferable to deployable system where data might be limited.

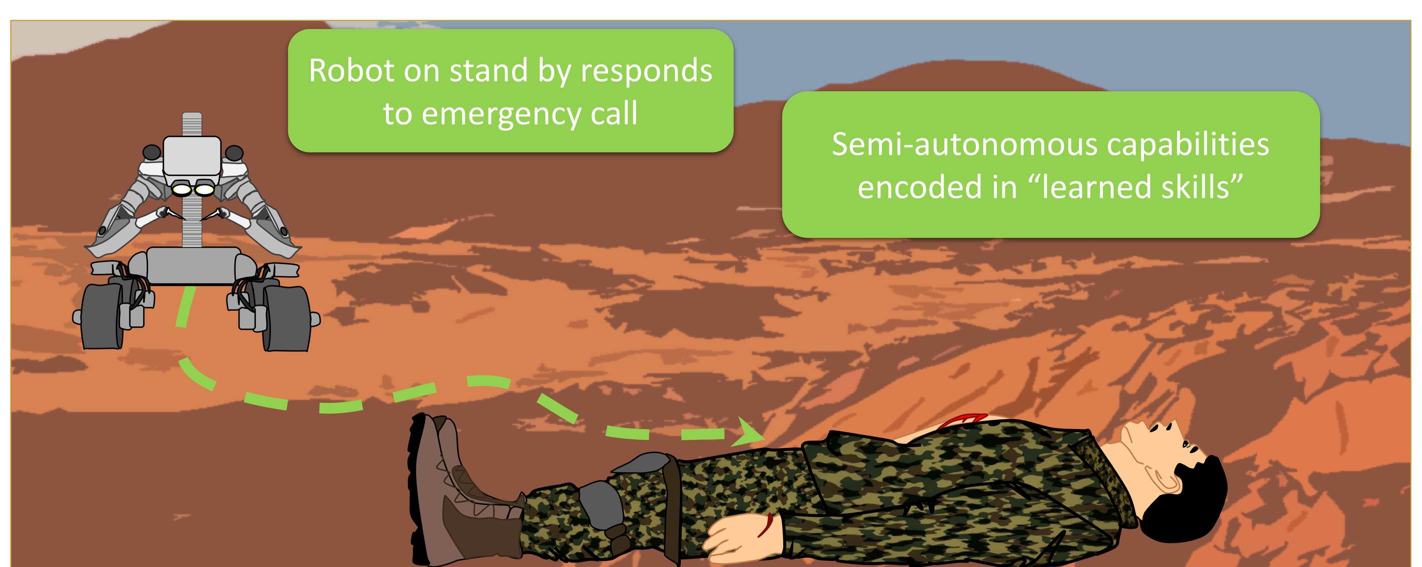

Figure 1. Deployable surgical robots on the battlefield

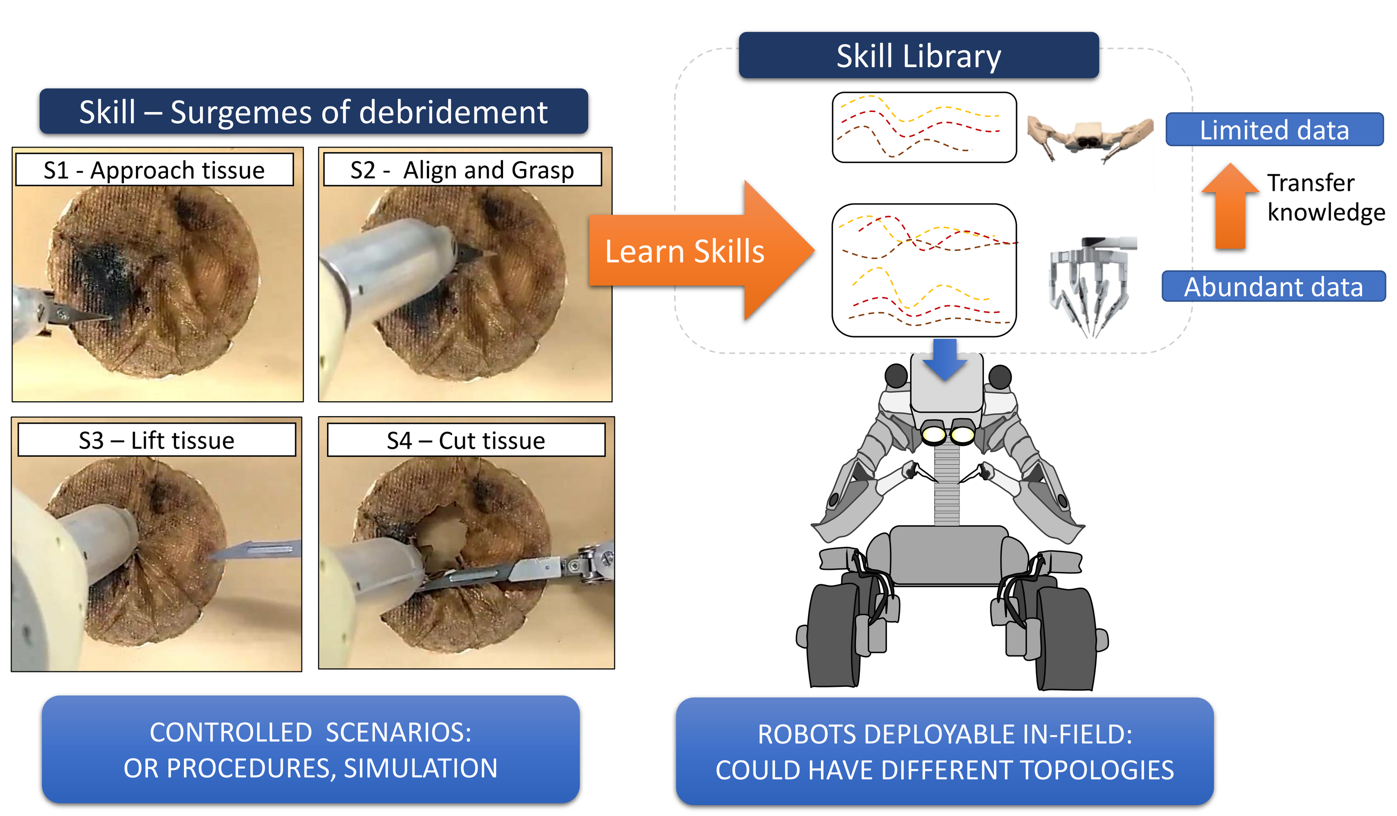

Figure 2. Library of robotic skills

Project Overview

We created the DESK (Dexterous Surgical Skill), a database of surgical gestures collected using three diverse robotic platforms.

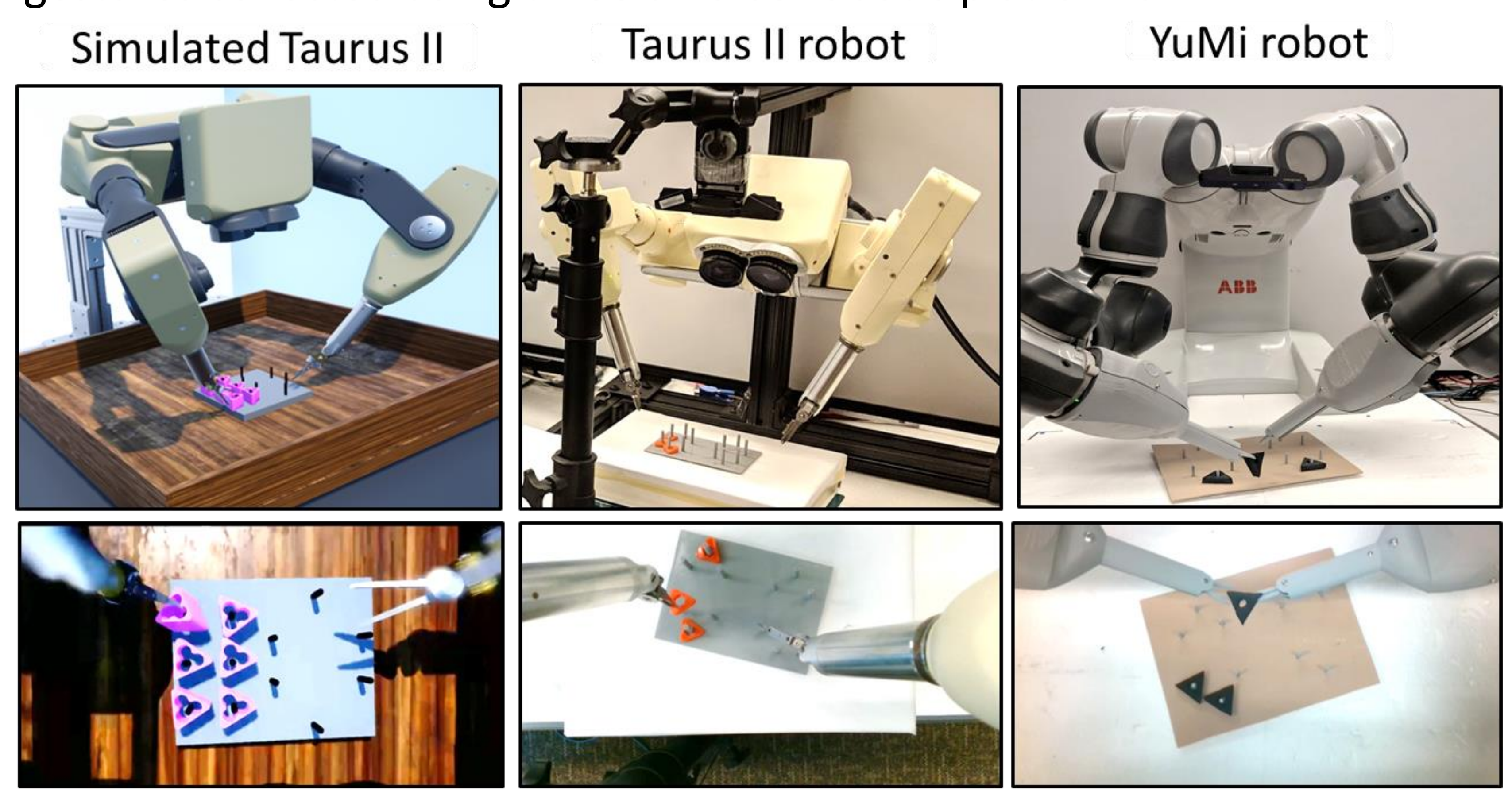

Figure 3. Robot systems in the DESK dataset

We trained three supervised models using two sets of features:

Features used	Models Trained
Kinematic information	Support Vector Machines (SVM)
Kinematic information + image features from a Convolutional Neural Network (CNN)	Random Forest (RF)
	Multilayer Perceptron (MLP)

Our experiments displayed the knowledge transfer of surgical skills from source (controlled domain) to target scenario (potentially austere). The source domain was a simulated Taurus platform, and the target domain were the real robots (Taurus and YuMi). The models were trained with data coming from the simulator and real domains.

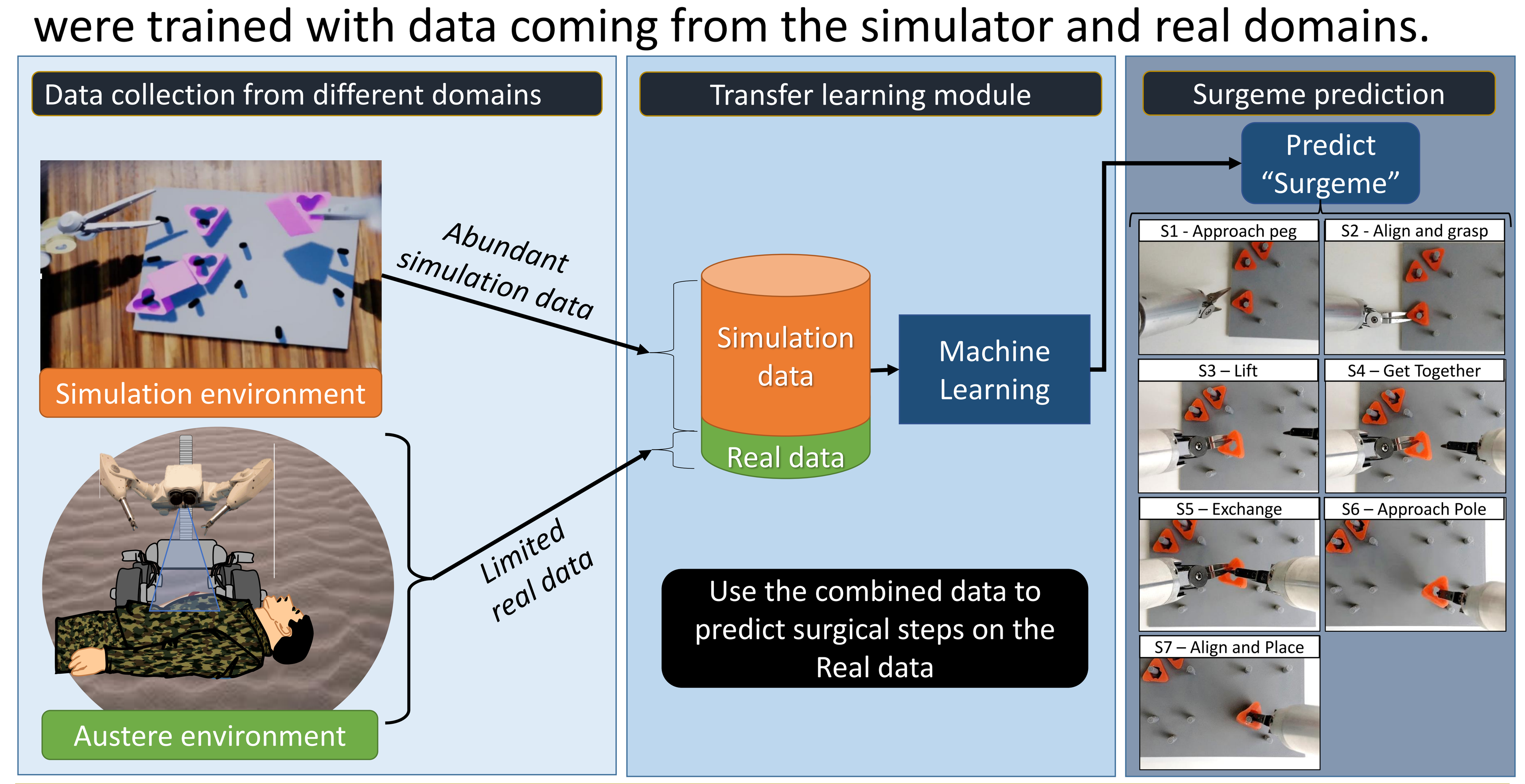

Figure 4. Transfer learning for surgeme classification

Results on Transfer learning

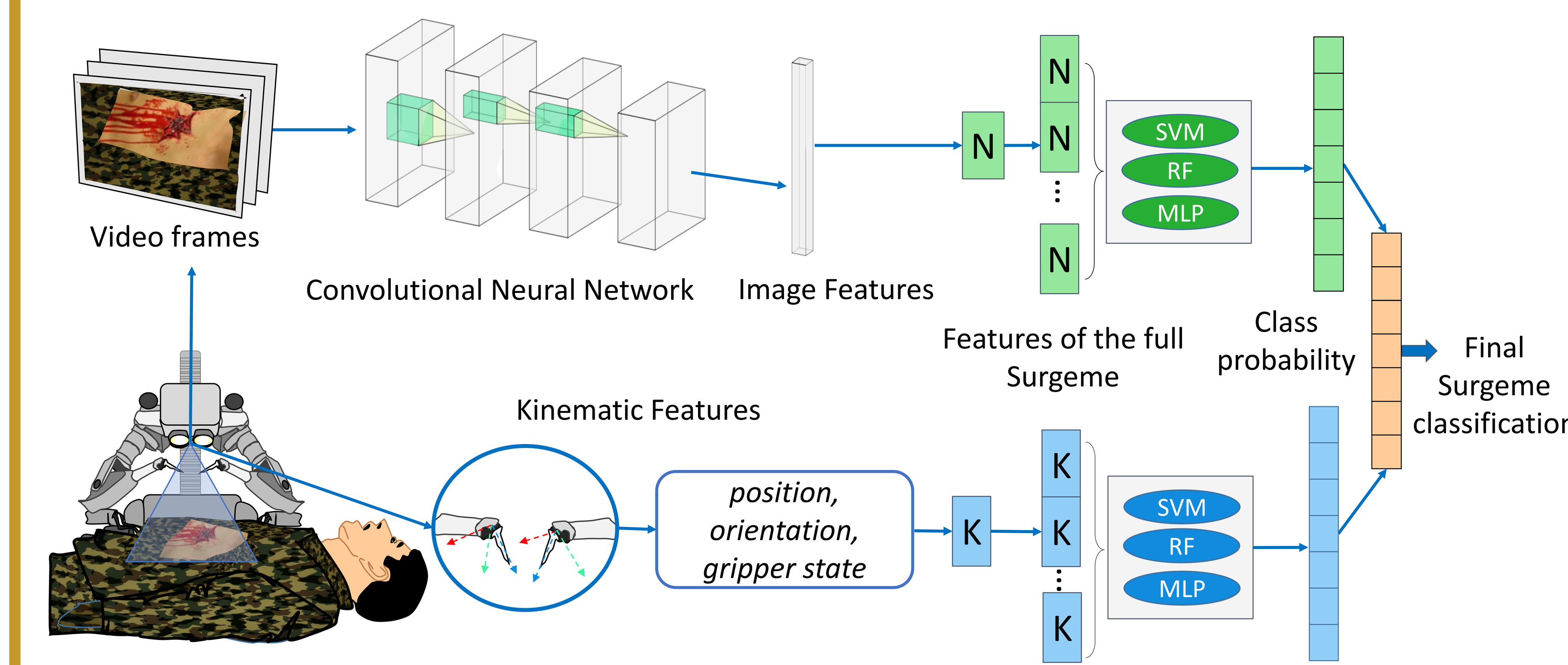

Figure 5. Architecture of machine learning framework for surgme classification

Surgeme classification results show that using simulation data during training enhances the performance on the real robot with limited data. We obtained an accuracy of 55% on the real Taurus training only on simulator data, yet that accuracy improved to 82% when the ratio of real to simulated data was increased to 0.18 in the training set. The inclusion of image features increased the classification accuracy of the models solely based on robot kinematics.

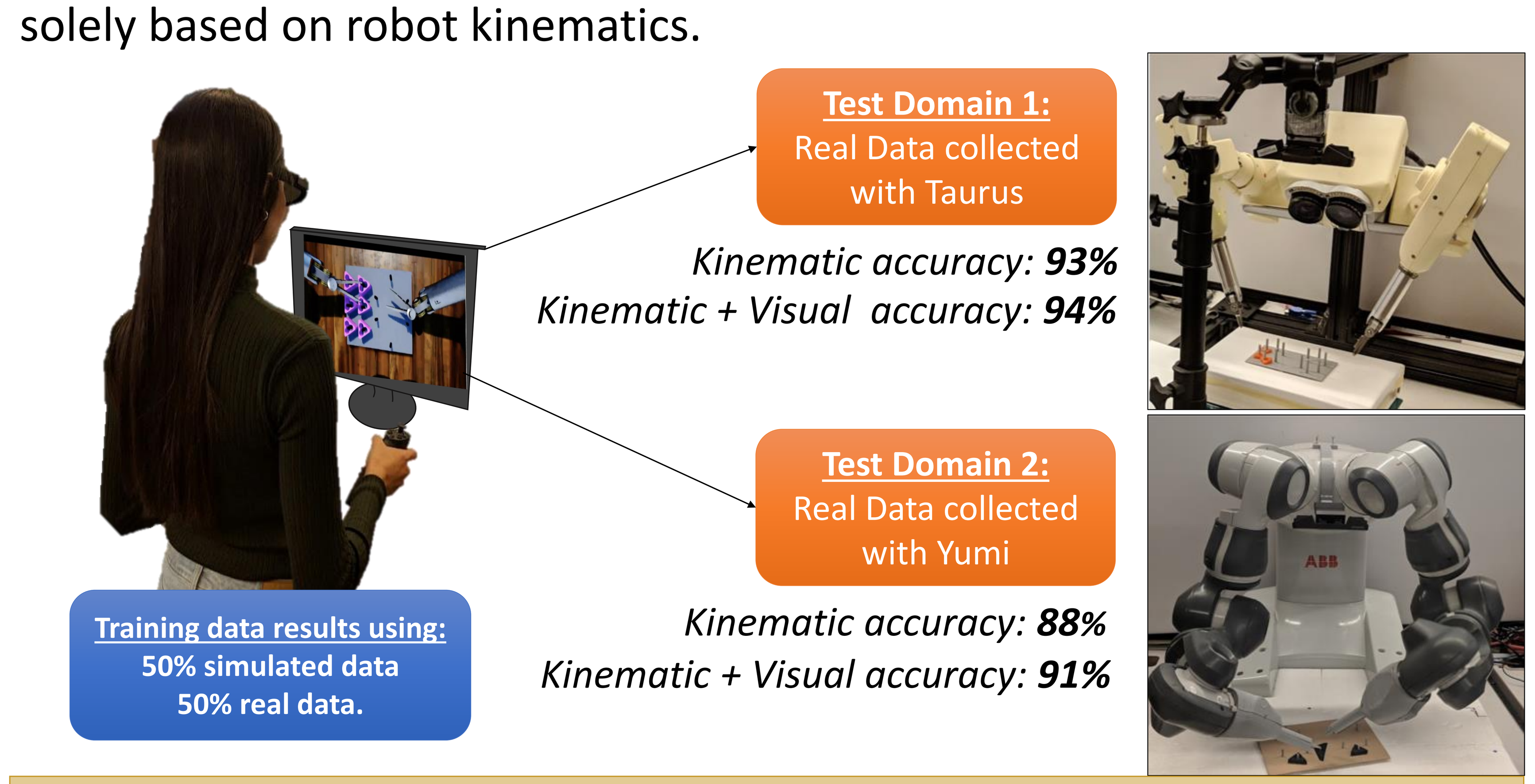

Figure 6. Results of skill transfer from controlled scenarios to dissimilar robotic platforms

Conclusions

Results show that the source domain can be used to augment the training data to build learning models in the target domain. The implications of this are that surgical data from the OR can be used for deployable surgical robots on the battlefield.

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