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Objective Assessment of Point-of-Care Ultrasound (POCUS) Competency Using Arm Motion Data and Machine Learning Classifiers

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Abstract

Point-of-care ultrasound (POCUS) is becoming an increasingly important tool for diagnostic evaluation, clinical decision-making, and procedural guidance in the emergency department (ED). POCUS image acquisition is cognitively demanding and operator-dependent, making rigorous competency assessment critically valuable. Traditional methods for assessing POCUS competency are limited by subjectivity, requiring a more objective approach. In this study, we aimed to investigate an objective method for assessing POCUS competency using arm motion data and employing machine learning (ML) classification methods. We utilized a motion-capturing system to extract motion data while ED clinicians performed POCUS tasks. We used logistic regression (LR) and random forest (RF) classifiers to predict the expertise level (expert versus novice) based on flexion, abduction, and pronation motion metrics from the right and left wrists and elbows. The mean accuracy of the LR model was 0.80 (95% CI [0.76, 0.84]) with an area under the curve (AUC) of 0.84. The mean accuracy of the RF model was 0.91 (95% CI [0.89, 0.93]) with an AUC of 0.95. These results suggest that both methods show promise for predicting the level of clinical expertise based on arm motion data during POCUS, with the RF model outperforming LR in terms of accuracy. Our finding

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highlights the potential of using motion capture data and ML approaches to objectively evaluate POCUS competency with high accuracy for distinguishing between novice and expert ED clinicians. Future studies should include larger sample sizes to further improve the accuracy of the models, as well as to investigate other ML techniques.

1 Introduction

Point-of-care ultrasound (POCUS) has become an essential tool for emergency medicine, facilitating rapid diagnostic evaluation, clinical decision-making, and procedural guidance (Andersen et al., 2019). However, the success of POCUS heavily relies on the operator's skills, making rigorous and objective competency assessment a critical need. POCUS credentialing has traditionally been based on a fixed number of scans, direct observation, and written examinations. These methods are often limited by biases and subjectivity, leading to inconsistencies in the results of the assessment (Rajamani et al., 2020). For example, benchmarks for the number of scans performed may not reflect the true competency level of an operator (Jensen et al., 2018). Moreover, competency assessments based on direct observation have limitations in feasibility, reliability, and scalability, which may lead to inflated assessments of competency (Norcini et al., 2011, Dashti et al., 2022). Thus, there is a need for an objective and standardized approach to POCUS competency assessment.

Motion capture technology has emerged as a promising tool for assessing clinical skill proficiency, both for technical and non-technical skills (Aggarwal et al., 2007; Saleh et al., 2008; Ezra et al., 2009; Berk et al., 2023, Ebnali et al, 2023). This technology utilizes sensors to capture and record the movement of a person's body during a task or procedure, providing an objective and standardized assessment tool. Early investigations of motion analysis demonstrated differences between experts and novices (Clinkard et al., 2015), and motion analysis has also been shown to correlate with expert assessments in POCUS performed by trainees (Vincent Baribeau & Murugappan, 2016). These studies offer promise towards the effectiveness of motion capture technology for objective POCUS skill assessment.

Furthermore, combining motion capture technology with machine learning (ML) models has the potential to provide an automated objective competency assessment tool in various healthcare applications(Berk et al., 2023; Ebnali et al., 2023, 2024), including POCUS operator proficiency(Carrie Walsh, 2024). ML models can be trained to evaluate POCUS skills, providing valuable feedback to enhance training and quality improvement (Drukker et al., 2021; Holden et al., 2019). These applications in POCUS competency assessment have the potential to make the assessment process more efficient, objective, and accurate(Driver, 2024; C. Walsh et al., 2024). While motion capture technology and ML have been proposed as promising alternatives to traditional assessment methods, research in this area is still in its early stages and requires further validation with larger, more diverse samples. Additionally, the practical feasibility of implementing these technologies in real-world clinical settings is yet to be fully established, and there is a need for more accurate and scalable solutions that can be integrated into existing POCUS assessment workflows.

In this study, we aimed to investigate an objective approach for assessing POCUS competency, using arm motion data and employing ML classification methods. The objective of this work was to predict the level of clinical experience (novices and experts) based on wrist and elbow motion data during POCUS tasks.

2 Methods

2.1 Study design and setting

This was a prospective, observational study conducted at a simulation center in an academic tertiary medical center. The medical center supports a 4-year emergency medicine residency program with 15 trainees per year and sees an ED volume of roughly 65,000 patients annually. This work was approved by the Mass General Brigham institutional review board (protocol number 2022P001347).

2.2 Participants

Participants were recruited via email advertisement sent to the local emergency medicine (EM) residency class of incoming interns as well as to faculty, fellows, and advanced practice providers (APPs) of the local emergency ultrasound fellowship program. All members of these groups were eligible to participate. Novice participants were defined as intern-level trainees with no prior formal experience in performing POCUS. Expert-level participants were defined as fellows or faculty who had completed at least a portion of emergency ultrasound advanced fellowship training, or APPs who had been practicing with the emergency ultrasound faculty for at least 3 years. After consenting to participate, participants completed recruitment surveys confirming their eligibility to participate and prior POCUS training to identify their level of expertise. Participants who did not meet criteria of either a novice- or expert-level sonographer as described above were excluded from the study.

2.3 POCUS tasks

In a simulation setting and on a standardized healthy model patient, participants were asked to perform two POCUS studies; an echocardiogram including five standard views (parasternal long axis, parasternal short axis, apical four axis, subxiphoid, and inferior vena cava), as well as a Focused Assessment with Sonography in Trauma (FAST) exam consisting of three standard views (a right upper quadrant, left upper quadrant, and pelvic). These studies were selected given their high utility and common application in EM clinical care. All participants were asked to perform the examinations holding the ultrasound transducer in their right hand with their left hand available to adjust machine settings as needed. Prior to performing POCUS, participants were fitted with the Rokoko motion capture system and the system was calibrated for each participant as described below. Participants and a POCUS machine (Mindray ME8, Mindray North America, Mahwah, NJ) were positioned to the right of a standardized patient lying supine on an exam table. Participants were given 120 seconds to achieve each POCUS view. The task for each view was ended and participants were instructed to move on to the next view either when they felt they had achieved as optimal a view as possible, or 120 seconds had elapsed. All examinations were video recorded using a GoPro camera (HERO11, GoPro, San Mateo, CA).

2.4 Motion analysis

The Rokoko motion capture system was used in this study to extract motion data during POCUS tasks. This system is a wearable technology that employs Inertial Measurement Unit (IMU) sensors to track joint movement and motion data. To ensure the safety of the participants and comply with COVID-19 guidelines, we did not use the full suit. Instead, we removed the sensors and cables from the Rokoko suit and fixed them onto the participants' bodies using straps. Calibration was performed to ensure accurate tracking of joint movement. During the data collection process, the participants were asked to perform the standardized POCUS studies tasks described above, while their motion data was recorded by the Rokoko system. The resulting motion data was stored in a standard data format, consisting of the x, y, and z coordinates of the sensors, and the adduction, flexion, and pronation of joints placed. In this study, we included 12 features related to the motion of the arms including flexion, abduction, and pronation data from both wrists and elbows of the participants using the Rokoko motion capture system.

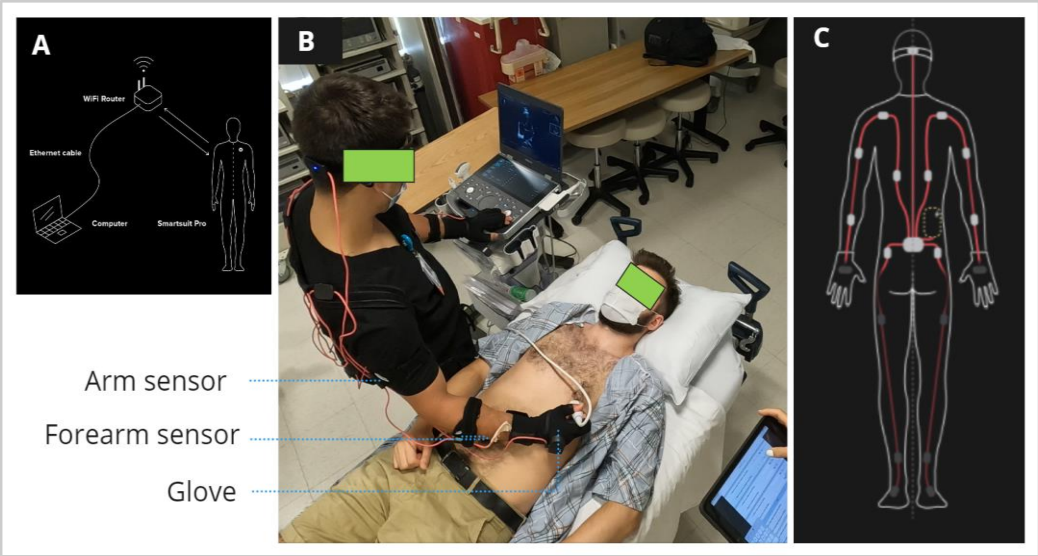

Figure 1: Nineteen IMU motion sensors connected to a hub (A, C); sensors fixed onto the participant' bodies using straps during POCUS task (B)

2.5 Classification methods

In this study, we used LR and RF methods to predict the level of clinical experience (expert vs novice) based on hand motion data collected during POCUS tasks. LR estimates the probability of a binary outcome variable based on one or more predictor variables, and the logistic function maps any real-valued input to a probability value between 0 and 1, representing the likelihood of the binary outcome variable taking on the value 1 given the predictor variables. On the other hand, RF is an ensemble method that combines multiple decision trees to improve classification accuracy. RF constructs numerous decision trees on different subsets of the data and predictor variables. The individual decision trees are then combined to produce a final prediction.

2.6 Modeling

We divided the data into training, validation, and testing sets to assess the performance of the LR and RF models. To mitigate the risk of overfitting, we used a 5-fold cross-validation method to evaluate the generalizability of the models. This involved splitting the data into 5 equal parts, with each part used as a validation set once while the other 4 parts were used as training data. This process was repeated 5 times, with each part used once as a validation set. The training set was used to fit the models, while the validation set was used to tune the hyperparameters of the models to maximize their performance. The test set was used to evaluate the final performance of the models.

Due to the nature of the study where novice participants had a longer completion time of the POCUS task compared to experts, the resulting dataset contained significantly more data points for the novice class, as noted by previous studies as well (Ackil et al., 2021). To address the class imbalance, a random sample of 1-minute data points for each participant was taken to ensure that the dataset was balanced between the novice and expert classes. We observed no evidence of multicollinearity among the variables in our analysis, as none of the correlation coefficients exceeded 0.7 or were less than -0.7 (Figure 2).

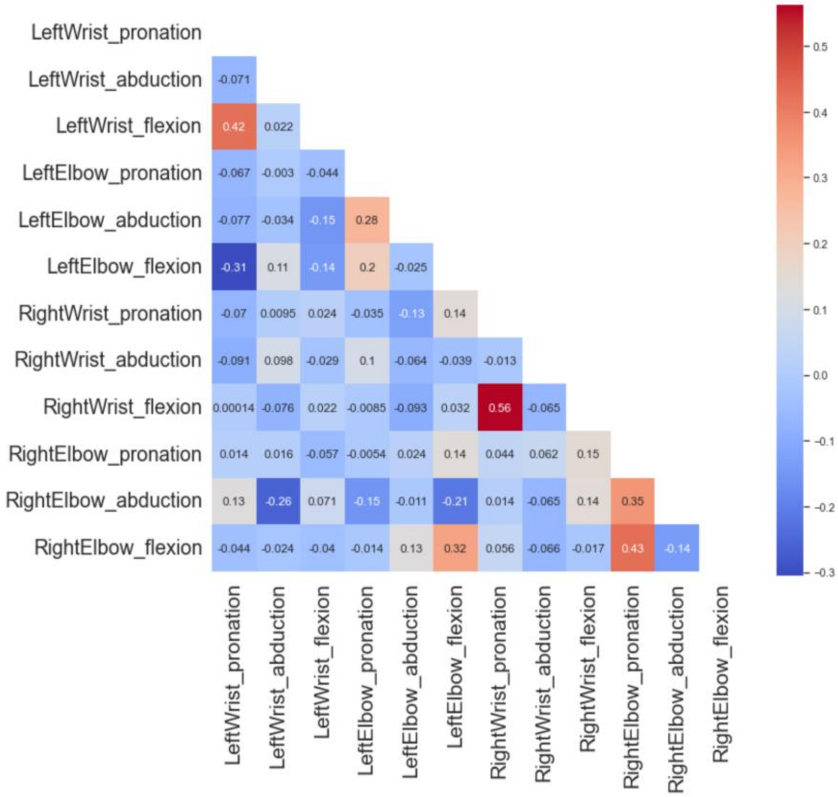

Figure 2: Correlation plot of arm motion features extracted from the Rokoko motion capturing system

3 Results

3.1 Participant demographics

In total, 8 novices and 9 experts were recruited. Among novices, the average age (+/- SD) was 26.8 +/- 1.6 years, 100% were right-hand dominant, and 88% completed a POCUS clinical rotation in medical school as their highest level of POCUS training prior to the study. Experts were 38.9 +/- 9.9 years in age, 77.8% were right-hand dominant, and 77.8% had completed some or all of an emergency POCUS fellowship as their highest level of POCUS training prior to the study. Novices reported completing an average of 14.2 +/- 11.3 echocardiogram studies and 14.9 +/- 10.1 FAST studies prior to participation. In comparison, experts reported performing an average of 1255.6 +/- 1341.7 echocardiogram studies and 1122.2 +/- 1124.5 FAST studies prior to participation.

3.2 Exploratory analysis

We observed statistically significant differences between expert and novice participants for selected variables ($p < 0.01$, Figure3). The median values for the majority of the variables were higher for expert participants, indicating that they perform the tasks with larger ranges of motion. The median values for left wrist pronation, right wrist flexion, and right elbow pronation were the highest among all variables, with values of 33.80, 34.24, and 17.90 degrees, respectively. The median values for left elbow abduction and left wrist abduction were the lowest among all variables, with values of -32.91 and -21.77 degrees, respectively. There were some exceptions to this pattern, such as left elbow flexion, where the median values were similar between expert and novice clinicians.

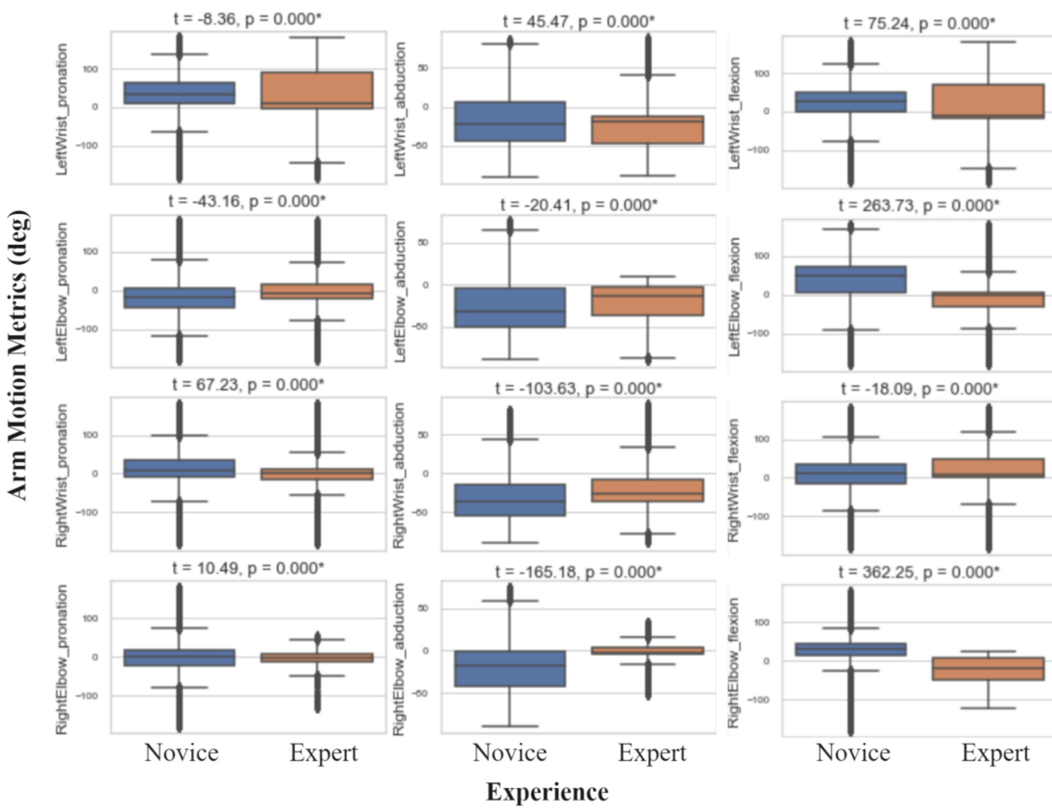

Figure 3: Comparison of arms motion feature between novice and expert participants

3.3 Classification performance

LR yielded a mean accuracy of 0.80 (+/- 0.04) with cross-validation scores ranging from 0.76 to 0.82 across five folds. The confusion matrix showed that 88.5% of novice participants were correctly classified, while 78.4% of expert participants were correctly classified. The root-mean-square error (RMSE) was 0.40, indicating that the model's predicted probabilities were, on average, 0.40 units away from the true probabilities. The AUC was 0.83, indicating a good overall performance of the model in distinguishing between expert and novice participants. The accuracy of the model was 0.84, indicating that the model correctly classified 84% of participants.

RF yielded a mean accuracy of 0.91 (+/- 0.02) with cross-validation scores ranging from 0.90 to 0.92 across five folds. The confusion matrix showed that 95.6% of novice participants were correctly classified, while 94.8% of expert participants were correctly classified. The RMSE was 0.22, indicating that the model's predicted probabilities were, on average, 0.22 units away from the true probabilities.

The AUC was 0.95, indicating an excellent overall performance of the model in distinguishing between expert and novice surgeons. The accuracy of the model was 0.95, indicating that the model correctly classified 95% of participants. These results suggest that the RF model outperformed the LR model in terms of accuracy and overall performance (Figure 4).

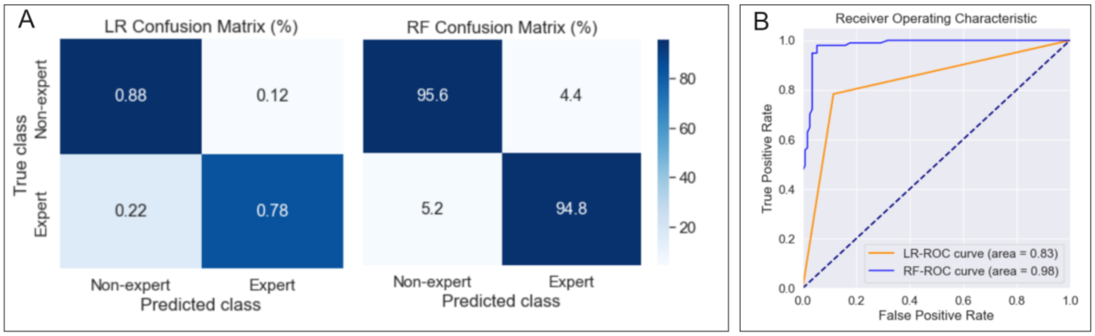

Figure 4: Confusion matrixes for LR and RF (A); ROC comparison of LR and RF models for POCUS competency assessment (B)

4 Discussion

We aimed to objectively assess POCUS competency by utilizing arm motion data captured by a motion-capturing system and ML classification methods. LR and RF classifiers were then employed to predict participants' expertise level based on flexion, abduction, and pronation metrics from the wrists and elbows.

Our exploratory analysis suggests that expert participants move their limbs through larger ranges of motion during POCUS image acquisition. One possible explanation is that experts are able to optimize their technique by holding the probe closer to the body, allowing for larger motions and potentially faster completion of the task. However, the differences between expert and novice clinicians were not consistent across all variables, suggesting that the range of motion may be task-specific. These results are consistent with previous research highlighting the significant impact of experience on the development of motion patterns associated with clinical expertise (Good et al., 2019). However, our small sample size and the varying nature of the tasks may contribute to inconsistent findings in previous studies regarding the relationship between the range of motion and experience (Ackil et al., 2021; Chin et al., 2011). It is worth noting that there may be different findings when analyzing procedural POCUS, as this may require a different set of biomechanical skills compared to POCUS image acquisition. Further research may be necessary to compare the differences in hand motion patterns between the two types of procedures.

Our results also indicate that LR and RF models are effective in distinguishing between expert and novice clinicians in POCUS tasks. The RF model outperformed the LR model in terms of accuracy and overall performance. One possible explanation for this finding is that the RF model is better equipped to handle non-linear relationships and interactions between variables, which may be present in POCUS tasks. This finding is consistent with previous studies that have demonstrated the effectiveness of ML methods in automated assessment of POCUS skills such as methods based on decision trees and fuzzy inference systems predicting ultrasound operator skills (Holden et al., 2019). The application of ML in POCUS assessment is still limited and requires further investigation to fully assess the utility of these approaches in POCUS training and evaluation (Bowness et al., 2021; Brattain et al., 2018).

Hand motion analysis has been shown to differentiate novice and expert clinicians in various ultrasound procedural skills such as laparoscopic surgery, lumbar puncture, regional anesthesia, and central venous catheter placement (Aggarwal et al., 2007; Clinkard et al., 2015; Yeo et al., 2015). There is limited evidence for using arm motion analysis in assessing POCUS competency, despite its potential to measure the motor patterns required for this skill. A major barrier to the widespread adoption of arm motion analysis in POCUS has been the lack of necessary equipment in ED. However, the incorporation of IMU into ultrasound probes offers a promising solution, making hand motion analysis readily available for frequent and rapid assessment of POCUS image acquisition and procedural skills. Additionally, the application of computer vision methods in other fields, such as surgery, has demonstrated their potential in evaluating clinical skills at the individual (Gabrielli et al., 2011) and team levels (Dias et al., 2022), highlighting the potential for future advancements in the automated assessment of POCUS competency.

5 Limitations and Future Directions

Despite the promising results, our study has limitations. The small sample may limit the generalizability of our findings. Additionally, the study was conducted in a simulated environment using a simulated patient without pathology, and it is possible that the results may differ in a real-world clinical setting. Future studies with larger sample sizes and in real-world clinical settings are needed to validate the findings of our study and determine the feasibility of implementing ML algorithms in arm motion data captured in clinical settings. We also acknowledge that motion-capturing suits and gloves may not be practical for assessing POCUS competency in real-world clinical settings due to their potential to interfere with clinical workflow. However, we aim to use these metrics as ground truth for our future studies, which will focus on developing computer vision-based techniques for POCUS competency assessment using video data.

6 Conclusion

We have demonstrated the feasibility and potential of using motion capture data and ML methods as a promising approach to objectively evaluate POCUS competency with high accuracy. However, larger sample sizes and additional motion variables are necessary to enhance the accuracy of the model and compare the effectiveness of other machine learning techniques. Further research in this area has the potential to improve the quality of POCUS training and assessment, leading to better patient care outcomes.

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