

Detecting clinical medication errors with AI enabled wearable cameras

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Supplementary Materials

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Supplementary Table 1. Distribution of syringe drug labels in real-world operating room dataset and classifier training dataset.

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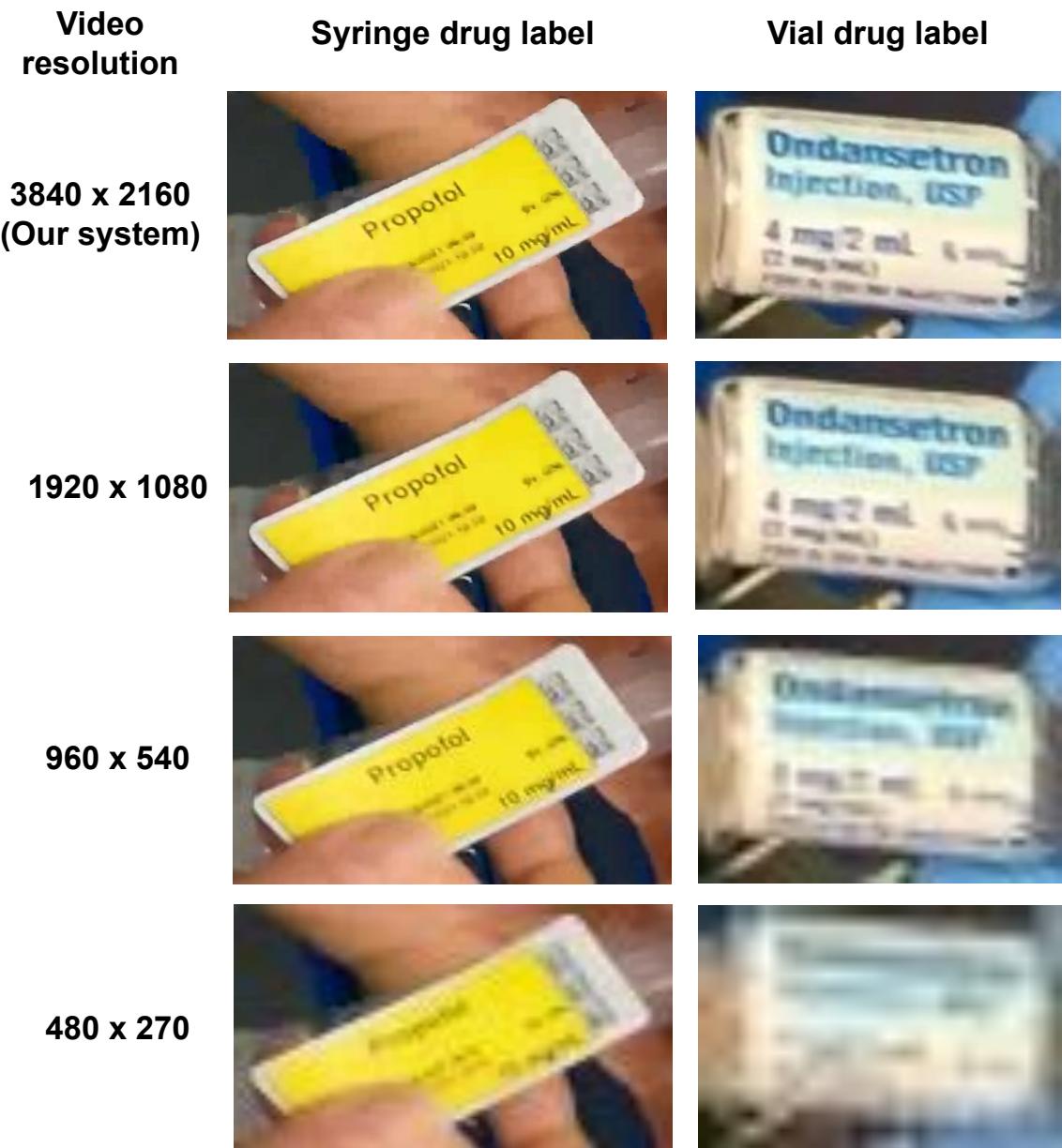
Supplementary Table 3: Distribution of syringe classifier training dataset images between real-world operating room and the controlled environment.

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Supplementary Algorithm 1: Algorithm to classify drug label on syringe or vial.

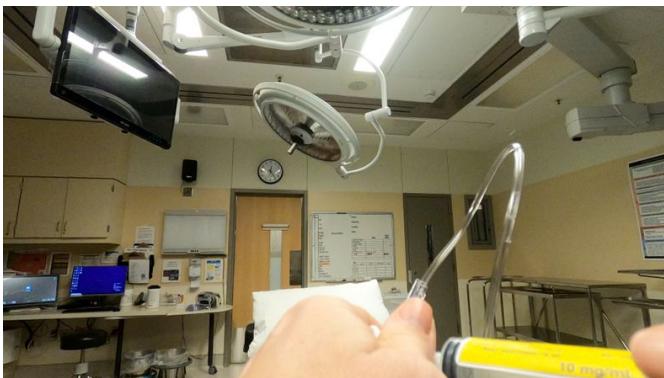
Supplementary Algorithm 2: Algorithm to compute vial swap errors.

Supplementary materials



Supplementary Figure 1 | Example drug labels at different resolutions. Labels captured at resolutions lower than the 4K video resolution used by our system can be difficult to read and classify.

a Chest-mounted camera



b Head-mounted camera tilted down



c Head-mounted camera facing straight



d Head-mounted camera tilted down



Supplementary Figure 2 | Camera view from different positions and angles. View of drug delivery event from **a**, chest-mounted camera and **b**, head-mounted camera tilted down. The head-mounted camera more reliably captures the drug label. View of a drug drawup event from head-mounted camera **c**, facing straight and **d**, tilted down. The drawup event is only visible when the camera is tilted down.

a Drug drawup with gloves



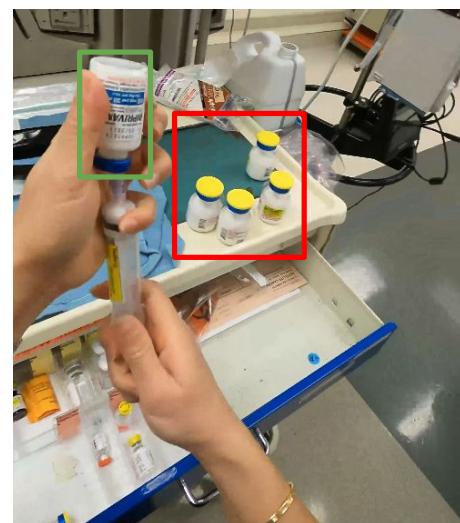
Drug drawup without gloves



b Syringes in background



Vials in background



Supplementary Figure 3 | Different drug drawup scenarios in realworld operating room conditions. Drug drawups when **a**, provider is and is not wearing gloves **b**, syringes and vials are present in the background. Background syringes and vials are marked with a red bounding box, and the syringe and vial in hand is marked with a green bounding box.



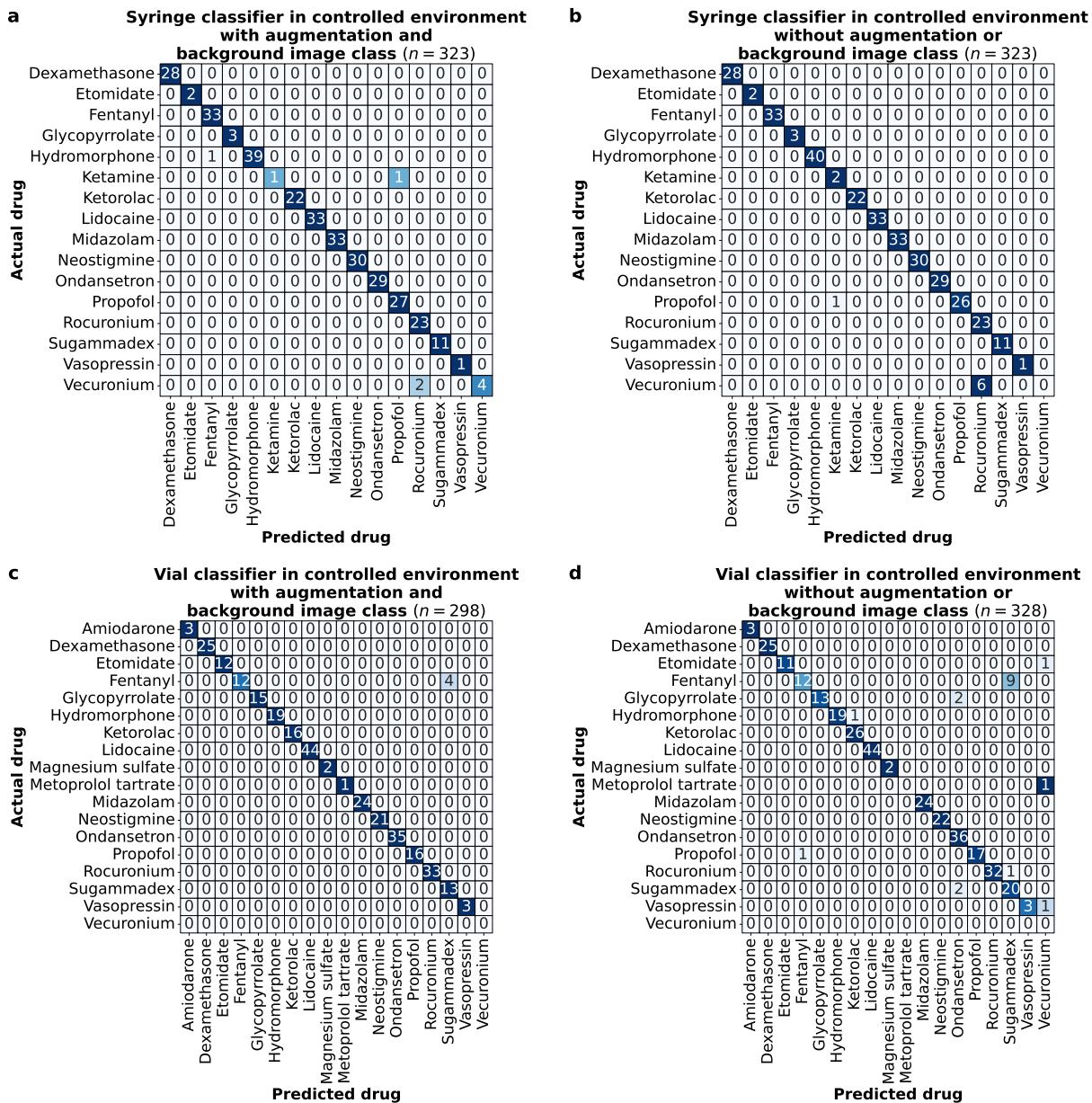
Supplementary Figure 4 | Example images of syringe drug labels in the dataset. Labels have different background colors, design layouts, lettering styles, and font choices.



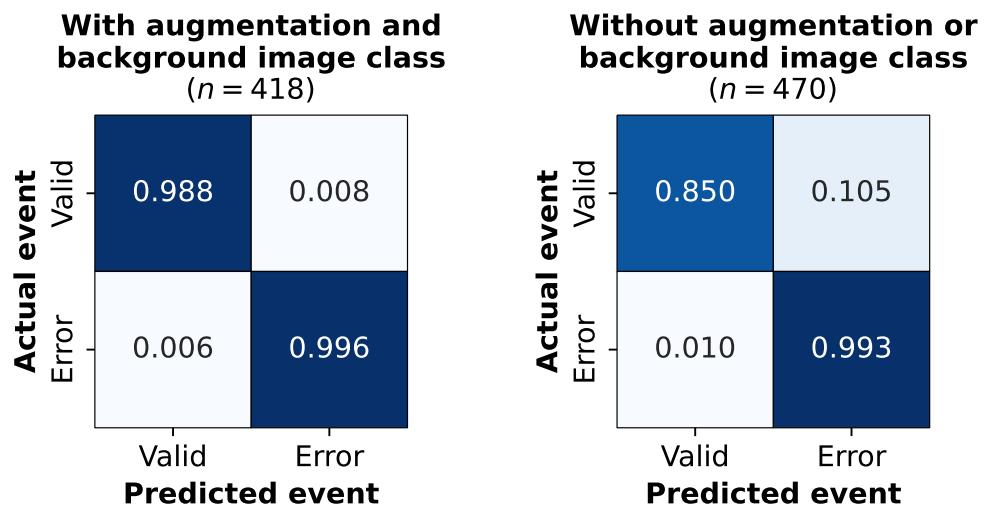
Supplementary Figure 5 | Example images of vial drug labels in the dataset. Labels span a variety of different background colors, design layouts, and font choices.



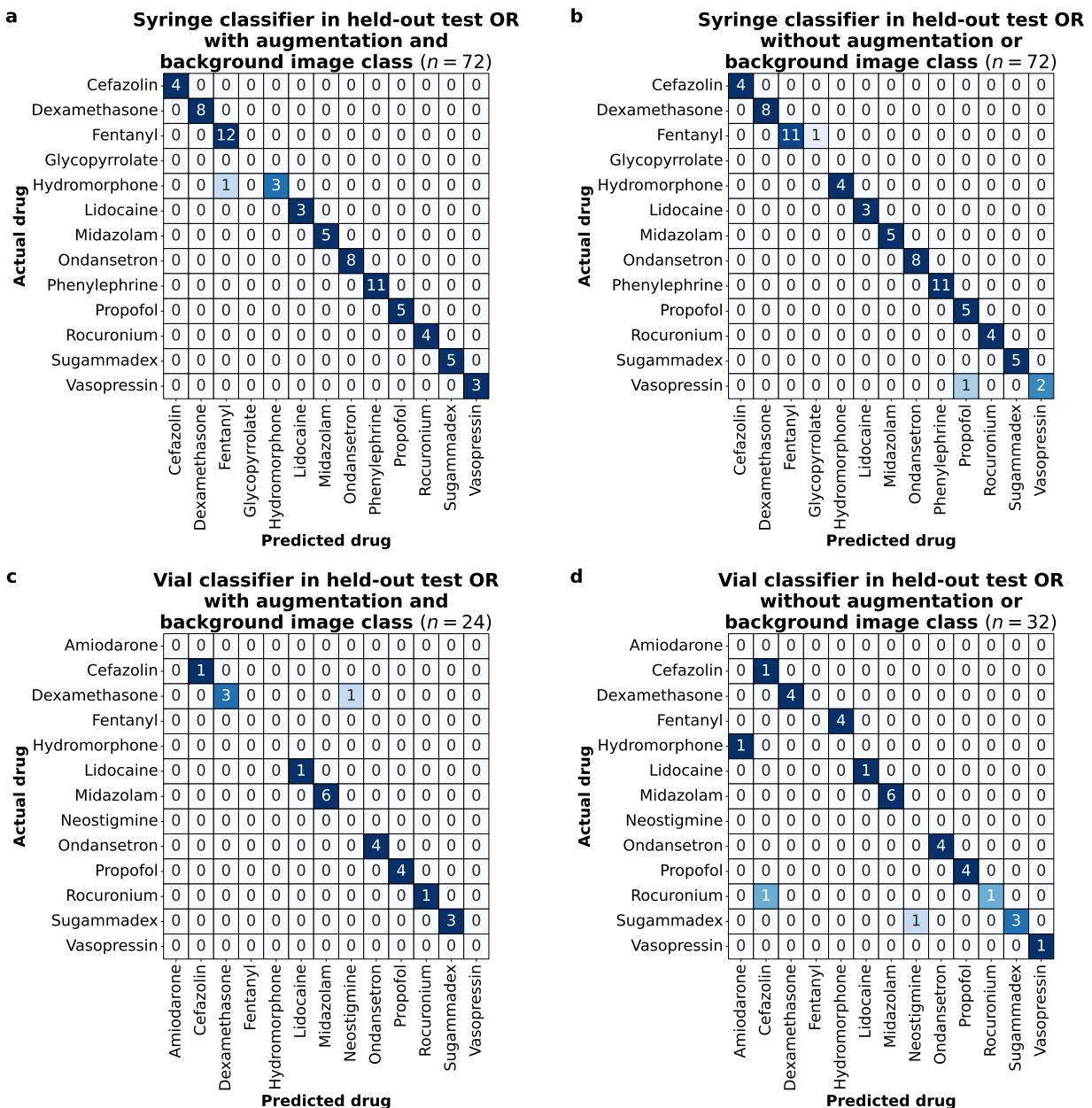
Supplementary Figure 6 | Example images of different vial labels styles for individual drugs in the dataset. The same drug can come in different vial shapes with different label designs. Labels can vary in dimension, background color, and font choice.



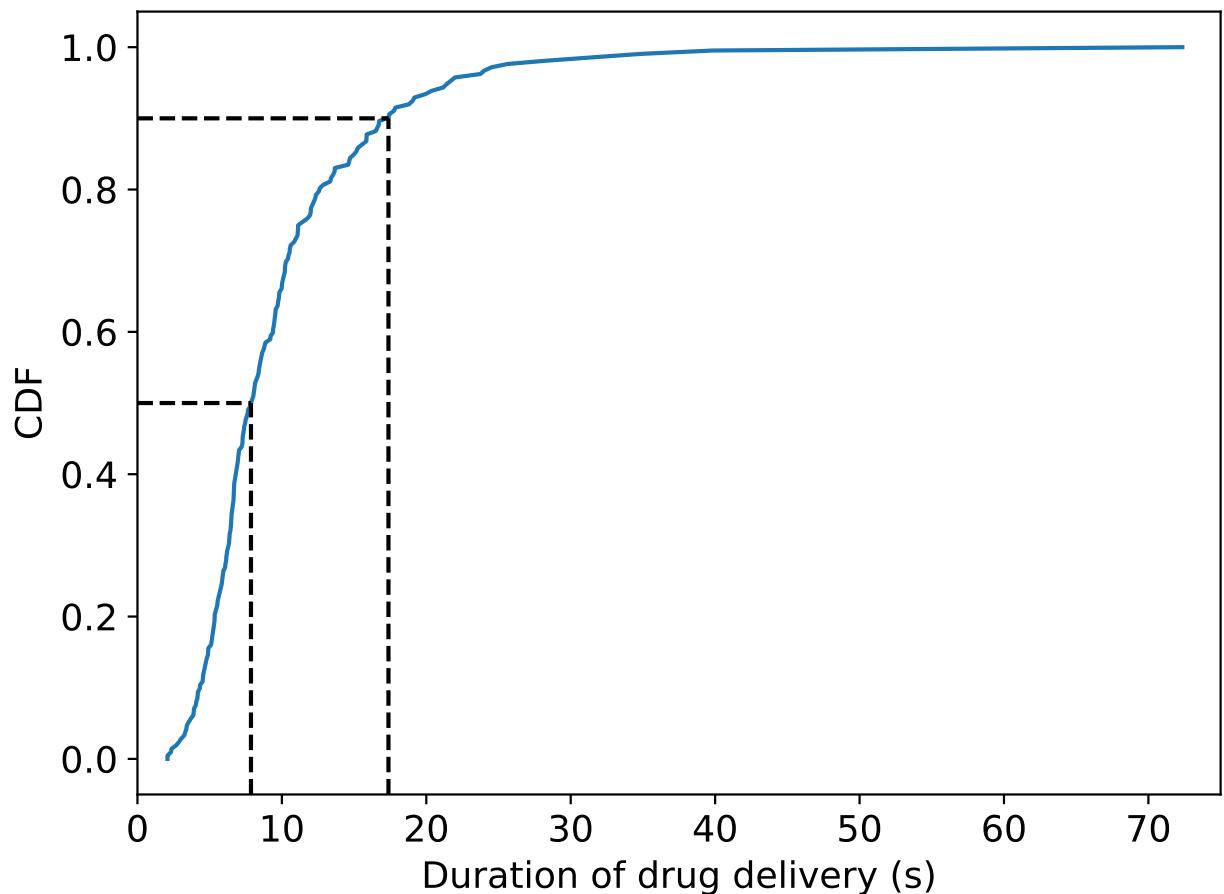
Supplementary Figure 7 | Drug label classification performance in controlled environment with vial swap events. Confusion matrices for **a, b** syringe labels with and without image augmentation and a background image class and **c, d** vial labels with and without image augmentation and a background image class.



Supplementary Figure 8 | Vial swap detection results across real-world operating room and controlled environment. Confusion matrices **a**, with augmentation and a background image class and **b**, without augmentation or background image class.



Supplementary Figure 9 | Generalization of drug label classifier performance to unseen hospital operating room environment. Confusion matrix for **a, b** syringe labels with and without image augmentation and a background image class and **c, d** vial labels with and without image augmentation and a background image class.



Supplementary Figure 10 | Cumulative distribution function of drug delivery duration ($n = 212$). The duration is computed as the time between when the syringe with the drug is picked up and when it is delivered into the patient. Duration information is collected across drug delivery events spanning a seven month period.

Drugs in training set			
Syringe drug label	Drawup events (n = 231)	Delivery events (n = 481)	# training samples (n = 10,180)
Cefazolin	0	0	492
Cisatracurium	0	0	360
Dexamethasone	23	27	397
Ephedrine	0	55	396
Epinephrine	0	0	343
Etomidate	0	4	430
Fentanyl	40	82	438
Glycopyrrolate	3	23	469
Hydromorphone	4	14	583
Ketamine	2	2	290
Ketorolac	0	8	341
Lidocaine	41	16	325
Midazolam	15	0	453
Neostigmine	0	5	394
Ondansetron	26	46	364
Phenylephrine	0	58	525
Propofol	53	59	675
Rocuronium	22	47	397
Succinylcholine	0	3	284
Sugammadex	2	22	439
Vasopressin	0	8	318
Vecuronium	0	2	429
Background image	-	-	1,000
Drugs not in training set			
Syringe drug label	Drawup events (n = 0)	Delivery events (n = 4)	# training samples (n = 0)
Esmolol	0	3	0
Labetolol	0	1	0

Supplementary Table 1: Distribution of syringe drug labels in real-world operating room dataset and classifier training dataset. Number of drawup and delivery events, and number of training images for each syringe drug label.

Drugs in training set		
Vial drug label	Drawup events (n = 143)	# training samples (n = 66,480)
Amiodarone	0	1,544
Cefazolin	0	1,510
Dexamethasone	11	2,978
Etomidate	0	3,274
Fentanyl	30	3,797
Glycopyrrolate	4	774
Hydromorphone	0	2,153
Ketamine	1	2,688
Ketorolac	0	4,549
Lidocaine	21	3,662
Magnesium Sulfate	0	1,018
Metoprolol Tartrate	0	134
Midazolam	7	2,148
Neostigmine	0	5,974
Ondansetron	22	2,708
Propofol	30	2,260
Rocuronium	15	2,894
Sugammadex	2	199
Vasopressin	0	3,376
Vecuronium	0	7,489
Background image	-	11,317

Supplementary Table 2: Distribution of vial drug labels in real-world operating room dataset and classifier training dataset. Number of drawup events and number of training images for each vial drug label.

Drug label	Operating room	Controlled environment
Cefazolin	492	0
Cisatracurium	0	362
Dexamethasone	17	380
Ephedrine	88	308
Epinephrine	8	335
Etomidate	8	422
Fentanyl	98	340
Glycopyrrolate	140	329
Hydromorphone	81	502
Ketamine	4	286
Ketorolac	40	301
Lidocaine	29	296
Midazolam	78	375
Neostigmine	14	380
Ondansetron	27	337
Phenylephrine	43	482
Propofol	206	469
Rocuronium	99	298
Succinylcholine	9	275
Sugammadex	87	352
Vasopressin	318	0
Vecuronium	0	429

Supplementary Table 3: Distribution of syringe classifier training dataset across evaluation environments. Number of syringe label images between real-world operating room and the controlled environment for each syringe drug label in the dataset.

Drug label	Operating room	Controlled environment
Amiodarone	0	1,544
Cefazolin	1,510	0
Dexamethasone	521	2,457
Etomidate	740	2,534
Fentanyl	911	2,886
Glycopyrrolate	0	774
Hydromorphone	0	2,153
Ketamine	504	2,184
Ketorolac	0	4,549
Lidocaine	580	3,082
Magnesium Sulfate	0	1,018
Midazolam	0	2,148
Neostigmine	316	5,658
Ondansetron	394	2,314
Propofol	270	1,990
Rocuronium	225	2,669
Vasopressin	0	3,376
Vecuronium	0	7,489

Supplementary Table 4: Distribution of vial classifier training dataset across evaluation environments. Number of vial label images between real-world operating room and the controlled environment for each vial drug label in the dataset.

Algorithm 1: Algorithm to classify drug label on syringe or vial.

```
Function drug_label_classifier (frames, drug_label_detector,
    drug_label_classifier, detection_probability_threshold, minimum_prediction_probability,
    minimum_drug_label_frames) :
    Input : frames Extracted video frames
    Input : drug_label_detector Drug label detector for syringe or vial
    Input : drug_label_classifier Drug label classifier for syringe or vial
    Input : detection_probability_threshold Probability threshold for drug label detector
    Input : minimum_prediction_probability Probability threshold for drug label classifier
    Input : minimum_drug_label_frames Minimum number of valid frames required to output a
        drug label prediction
    Input : classnames List of drug labels used by the classifier

    for frame ∈ frames do
        detection_probabilities, bounding_boxes ← drug_label_detector(frame)
        best_detection_probability_index ← argmax(detection_probabilities)
        detection_probability ← max(detection_probabilities)
        best_bounding_box ← bounding_boxes[best_detection_probability_index]

        if best_detection_probability > detection_probability_threshold then
            logits ← drug_label_classifier(best_bounding_box)
            classifier_probabilities ← softmax(logits)
            prediction_probability ← max(classifier_probabilities)
            prediction_index ← argmax(classifier_probabilities)
            predicted_class ← classnames(prediction_index)
            counter ← {}

            if predicted_class ≠ background and
                prediction_probability > minimum_prediction_probability then
                if predicted_class ∈ dict then
                    | counter[predicted_class] += 1
                else
                    | counter[predicted_class] ← 1

            most_common_class ← argmax(counter)
            most_common_class_frequency ← counter[most_common_class]

            if most_common_class_frequency ≥ minimum_drug_label_frames then
                return most_common_class
            return None
```

Algorithm 2: Algorithm to compute vial swap errors

Function *detect_vial_swap* (*frames*, *syringe_label_detector*, *vial_label_detector*,
syringe_label_classifier, *vial_label_classifier*) :

Input : *frames* Extracted video frames
Input : *syringe_label_detector* Syringe label detector
Input : *vial_label_detector* Vial label detector
Input : *syringe_label_classifier* Syringe label classifier
Input : *vial_label_classifier* Vial label classifier

syringe_detection_probability_threshold $\leftarrow 0.85$
vial_detection_probability_threshold $\leftarrow 0.8$

minimum_prediction_probability $\leftarrow 0.999$

minimum_syringe_frames $\leftarrow 1$
minimum_vial_frames $\leftarrow 6$

syringe_label_classification \leftarrow *drug_label_classifier*(
 frames, *syringe_label_detector*, *syringe_label_classifier*,
 syringe_detection_probability_threshold, *minimum_prediction_probability*,
 minimum_syringe_frames, *syringe_classnames*)

vial_label_classification \leftarrow *drug_label_classifier*(
 frames, *vial_label_detector*, *vial_label_classifier*,
 vial_detection_probability_threshold, *minimum_prediction_probability*,
 minimum_vial_frames, *vial_classnames*)

if *syringe_classification* \neq *None* and *vial_classification* \neq *None* **then**
 if *syringe_classification* = *vial_classification* **then**
 return *No error*
 else
 return *Vial swap error*
return *Event not classified*
