Object Detection in Sterile Compounding Areas

MSCS Final Group #2
Team: Andrew Waggoner, Kyle Russell, and Bob Owens
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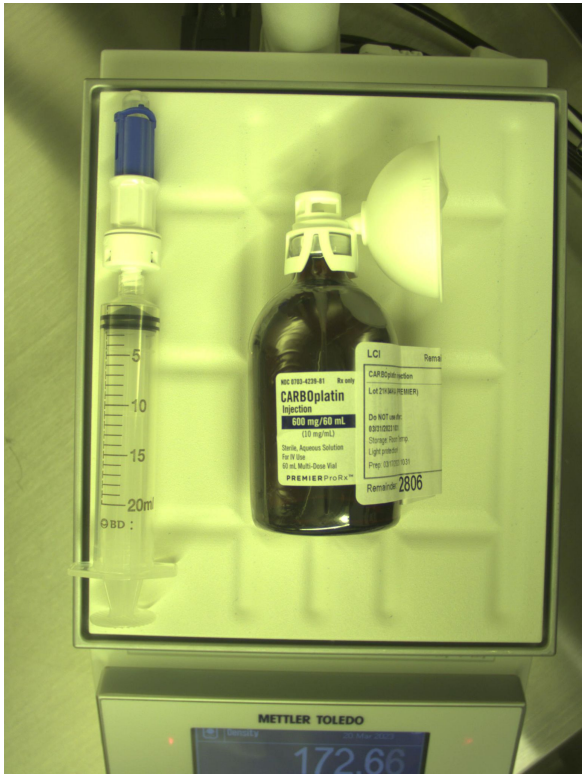
Motivation/Background

- Intravenous medications (IV) are prepared in especially controlled, highly regulated, sterile environments in hospital pharmacies
- In most hospital pharmacies, pharmacists must verify all doses before they leave the pharmacy
- Several technologies have been developed and employed to ensure accuracy with minimal disruption in the sterile environment
- Current gold standard methods include some or all of the following:
  - Gravimetric analysis
  - Barcode scanning
  - Remote camera viewing
- Related works focus on identification with RCNN, FCNN, or combination and none of them were oriented towards verification
- Can computer vision add an additional verification check that lessens the pharmacists burden in the IV room?

Data Set – Examples



Methods

- Obtained approximately 4,700 images taken in hospital IV rooms
- Labeled the images with Roboflow and then Label Studio
- Trained a YOLO (version 8) model on 1,000 labeled images
    - Model summary: 225 layers, 3,018,648 parameters, 3,018,632 gradients, 8.2GFLOPs
- Used the trained model to label more images with ML assisted labeling
- Adjusted labeling when needed, i.e. rotating the bounding boxes
- Retrained model, added more labels via predictive labeling, etc.
- We tested the model versus a validation set and unlabeled images not used in the previous steps
    - Train/test/validation split 80/10/10

Initial Findings

- Initial classifications with the COCO dataset put a bounding box around vials, but incorrectly labeled them as bottles
- With a few custom (#20) labeled images, training accuracy improved significantly
- With #50 custom labeled images the model was able to detect vials and syringes on a fairly consistent basis
    - Some of the less commonly labeled items in the images still had a low hit rate (mAP)
    - Additional labeled data was needed

Findings (cont.)

- We passed correctly classified images back in as additional training data
- We also decided to use the ML-assisted labeling to increase our labeled data set dramatically (ended up with 1,000 labeled images)
- We experimented with different numbers of epochs and more than 100 showed no improvement
- Many classes had few labels in the images we trained. (40 different classes)
- After 700 labeled images, YOLO became much better at classifying certain objects, (bags, syringes, common medicines in bottles)

Results-Validation

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Model summary (fused): 168 layers, 3013838 parameters, 0 gradients, 8.1 GFLOPs
                 Class     Images  Instances      Box(P          R      mAP50  mAP50-95):
100%|███
                   all         93        170      0.942      0.922       0.99      0.897
0.9% Sodium Chloride Injection USP         93         12      0.909      0.917      0.933
0.766
5% Dextrose Injection USP         93          5      0.805      0.832      0.962
0.747
      Arsenic Trioxide         93          1          1          1      0.995      0.895
           Azacitidine         93          1      0.912          1      0.995      0.895
      Cyclophosphamide         93          2          1      0.596      0.995      0.895
            Folic Acid         93          1      0.904          1      0.995      0.995
          Iron Sucrose         93          1      0.905          1      0.995      0.995
    Leucovorin Calcium         93         17          1      0.909      0.958      0.881
               Levemir         93          4      0.968          1      0.995      0.968
          Levetiracetam         93          1       0.91          1      0.995      0.995
                 Ogivri         93          2          1          0      0.995      0.703
            Ondansetron         93          1      0.901          1      0.995      0.995
            Oxaliplatin         93          3          1      0.958      0.995       0.56
             Paclitaxel         93          1      0.914          1      0.995      0.995
                PhaSeal         93         13      0.996          1      0.995      0.852
  Potassium Phosphates          93          1      0.927          1      0.995      0.995
         Sterile Water          93          3      0.954          1      0.995      0.908
          Thiamine HCl          93          9      0.985          1      0.995      0.955
        Vancomycin HCl          93          2      0.936          1      0.995      0.995
           carboplatin          93          2      0.885          1      0.995      0.995
          exactamix bag         93          3          1      0.838      0.995      0.805
           flourouracil         93          1      0.811          1      0.995      0.995
irinotecan hydrochloride         93          1      0.961          1      0.995      0.895
               needle          93         29          1      0.922      0.995      0.805
         small_syringe         93          3       0.96          1      0.995      0.871
               syringe         93         50          1      0.934      0.983      0.879
            vedolizumab         93          1      0.898          1      0.995      0.995
Speed: 1.8ms preprocess, 0.4ms inference, 0.0ms loss, 0.7ms postprocess per image
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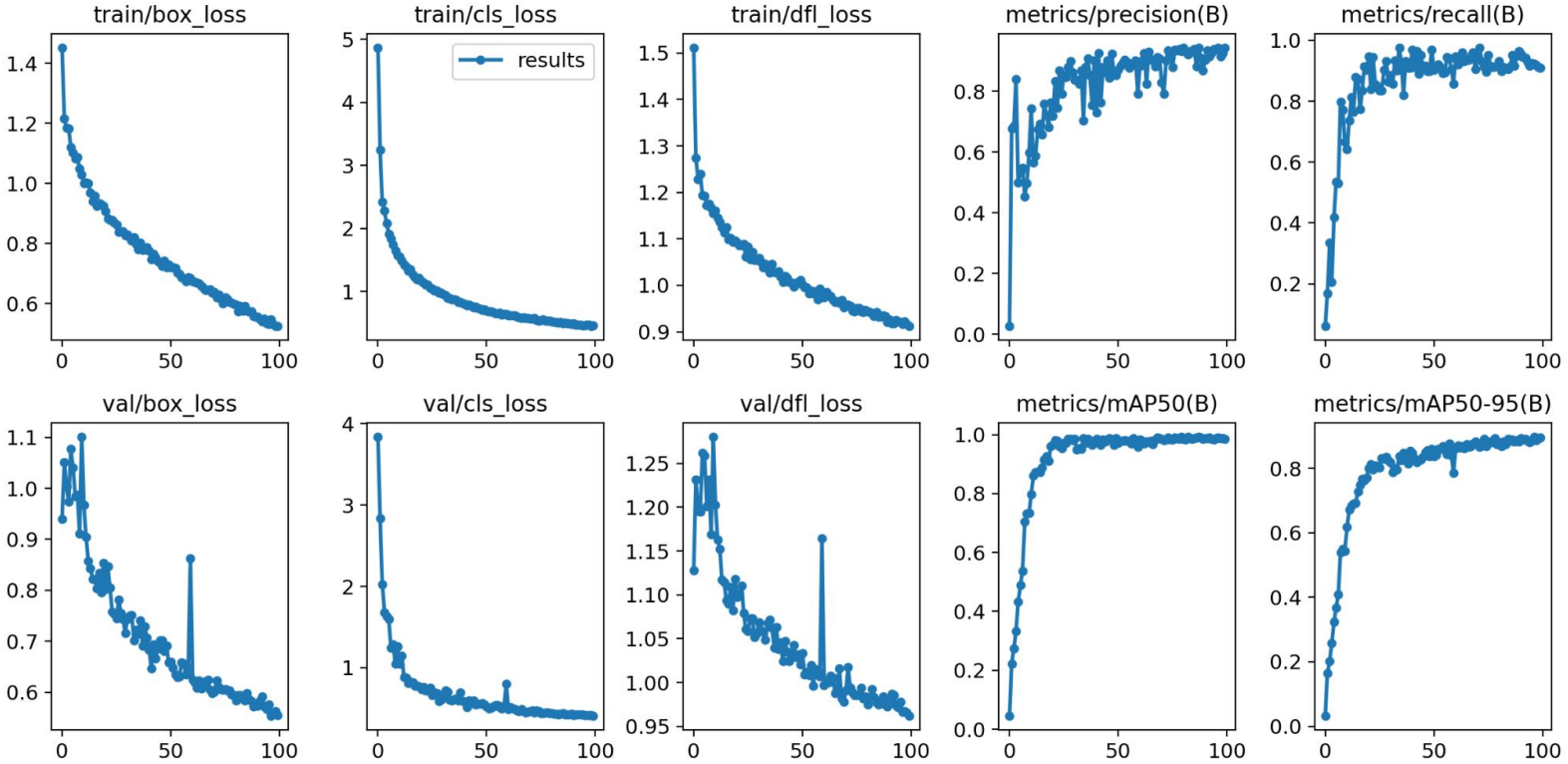
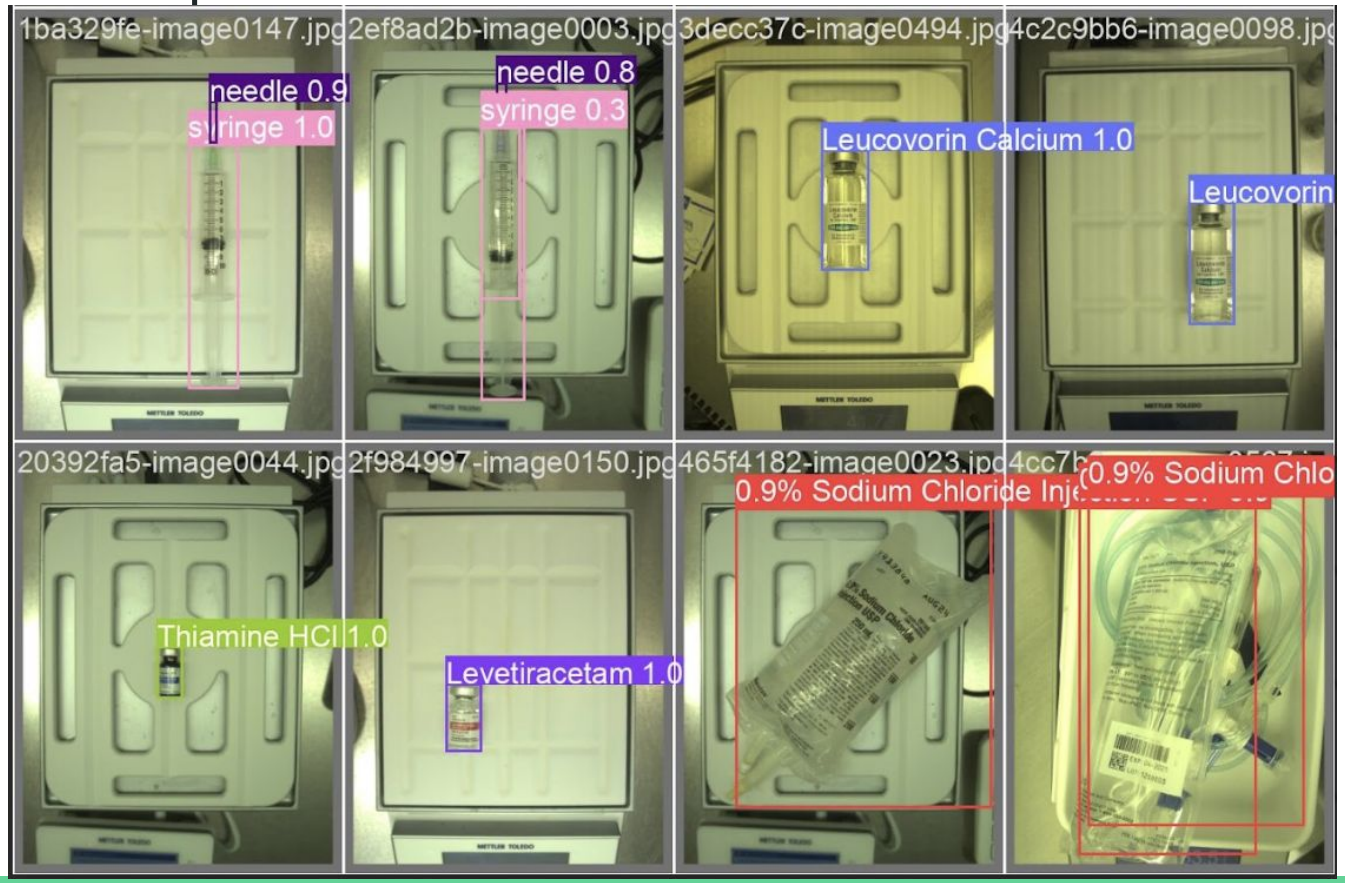
Results-Validation



Examples of results



Conclusion/Future Work

- Results can be further improved with additional labeled data
- Testing with real time classification using a handheld device like a smartphones
- Using segmentation prior to classification to see if we can determine how much liquid is in the syringe
- See if a model can be specific enough to detect changes in light refractivity of the resulting solutions.