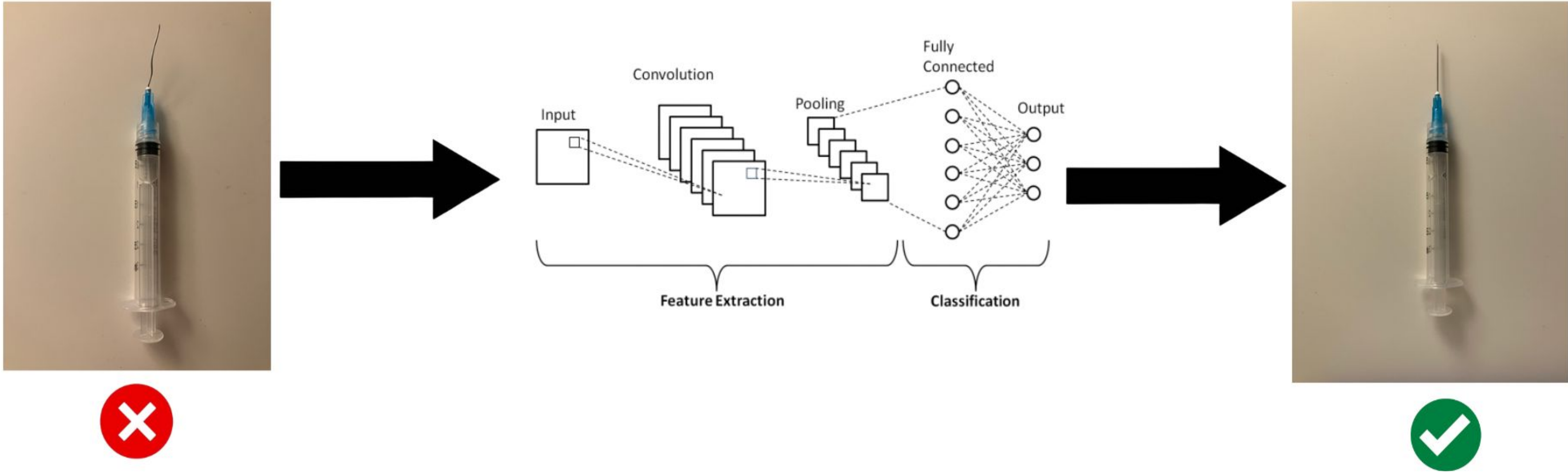
Graphical Abstract



Background Info

1

Automated production of goods has become much more common with recent advancements in technology

2

Computer error, however, can prevent automated manufacturing from being completely human-independent. Machines can incorrectly fabricate components due to poor materials or equipment failure, for example.

3

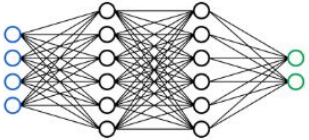
Currently, humans are commonly tasked with detecting defects in freshly made products. However, laborers can experience fatigue while scanning objects, and they can be costly to hire

4

In the medical industry, products should be scanned for defects before they are shipped out to hospitals. An important example of this is syringes. However, 1 out of every 200 syringes are defected, which is a lot when thinking about a large scale.

5

A Convolutional Neural Network can be used instead, which is inexpensive to implement and is highly precise in finding defects



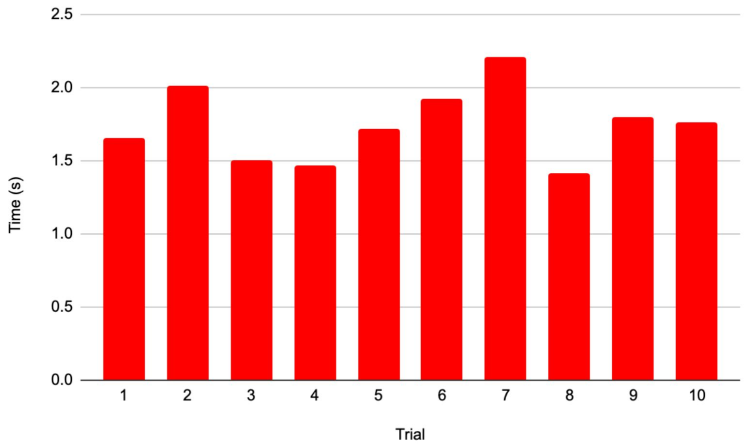
Website QR Code

Scan this QR code to see more information on my STEM project

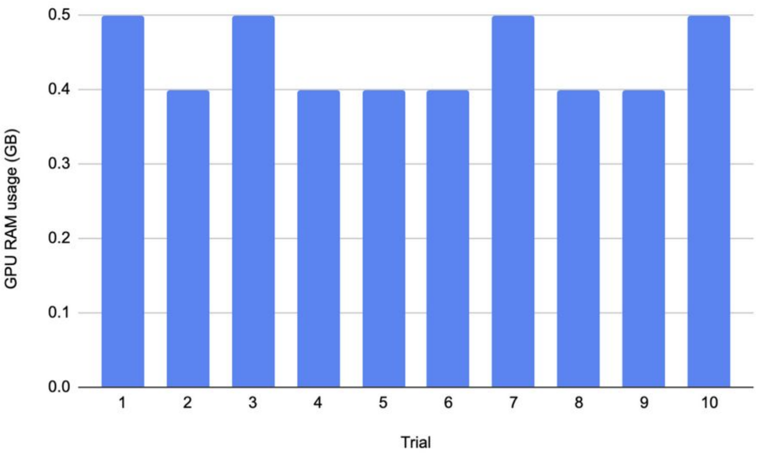
Prelim: Runtime With Given Hardware

The processing time was tested again using the current hardware available for this project. This helped determine the overall viability of the YOLO11 model for this project.

To test the image recognition processing time, ten trials were conducted using stock images of humans riding bicycles. Each trial's processing time is recorded to the right.



Prelim: RAM Usage With Given Hardware



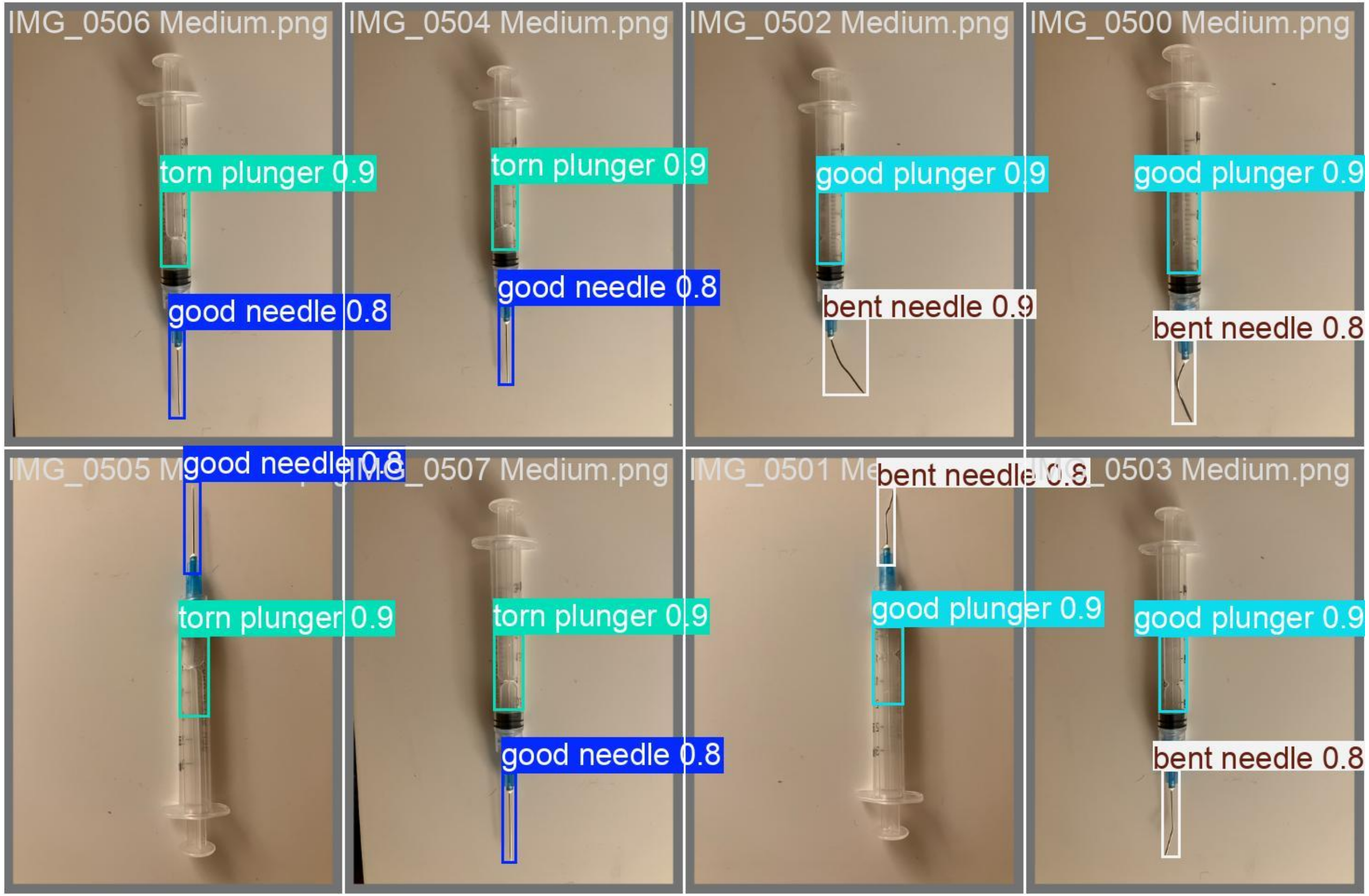
GPU RAM usage was remeasured for ten trials using the current hardware available. The cloud Tesla T4 GPU used had a max GPU RAM capacity of 1.5 gigabytes.

This is another criteria similar to the time criteria that helped ensure that the YOLO11 model was a good choice for this project. To the left is the results of the trials.

Conclusions: Accuracy

- Torn plungers, good plungers, and bent needles were detected accurately with a recall of 92% or above for these classes. The strong recall score for these classes demonstrates that the model performs well on detecting defective syringes, particularly because of its high rate of correctly finding bent and torn syringes.
- However, the model accurately finds good needles at a rate of only 80%. In the context of the problem, the issue is not that severe and is not as problematic as if the model was detecting defected syringes as non-defected.
- Nonetheless, the best approach for resolving this problem would be to add more training data related to needles.

Example Predictions



Conclusions on Processing Time

- According to the graph, the YOLO11 model has a faster inference time than many other object detection models, a large reason why this model would be a good fit for this project.
- The average total processing time was 1.748 seconds. Given that the average conveyor belt moves at 7 feet per second (National Safety Council, 2016) a syringe will travel around 12.24 feet before defect results are produced.
- Therefore, a camera that is elevated a few feet off the ground can determine if a syringe is safe or faulty when the syringe is just a few feet ahead of it. Immediately after detection, the syringe can be disposed of or kept for shipping.

Results: Confusion Matrix

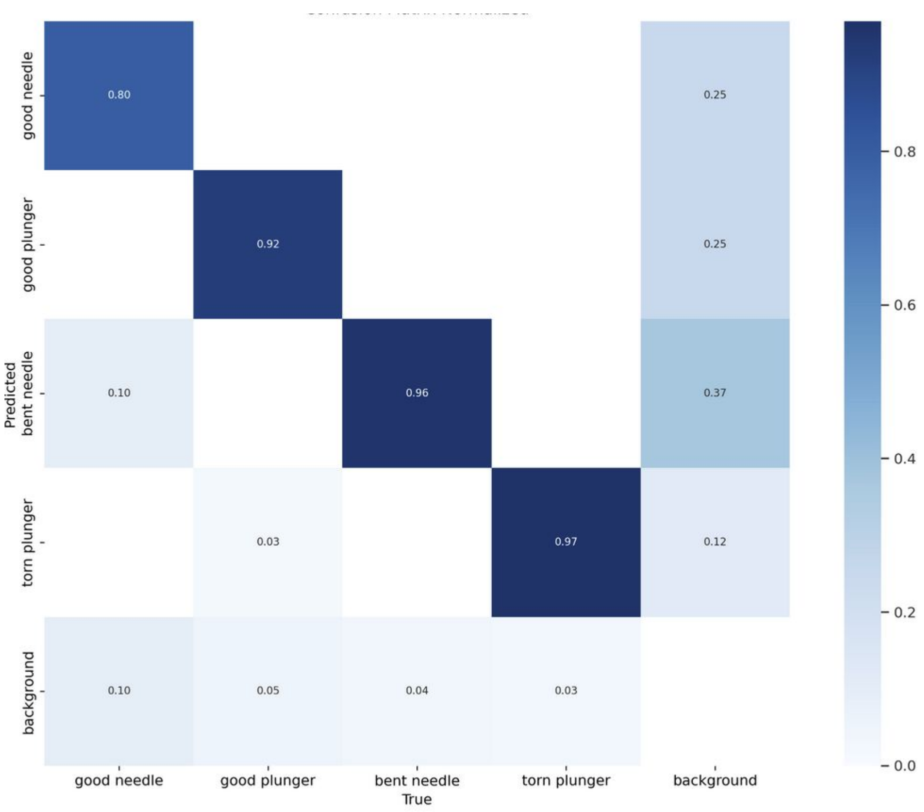


Figure 4: Confusion matrix detailing accuracy of model predictions for each class

- After training was completed, testing was run separately on the entire dataset to generate a confusion matrix.
- The model predicted good plungers, bent needles, and torn plungers with recall greater than 90%. However, good needles were detected accurately at a rate of 80%.

Results: mAP Score

- The model was in its learning phase from epochs 0-20. It plateaued starting from around epoch 50
- On its best epoch, reached a mAP score of 93%
- Higher mAP score indicates overall reliability of the model

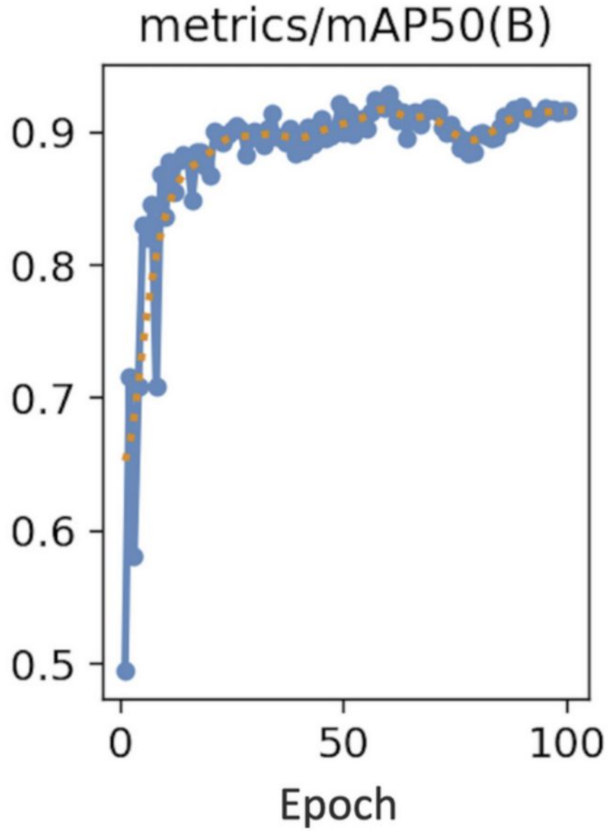
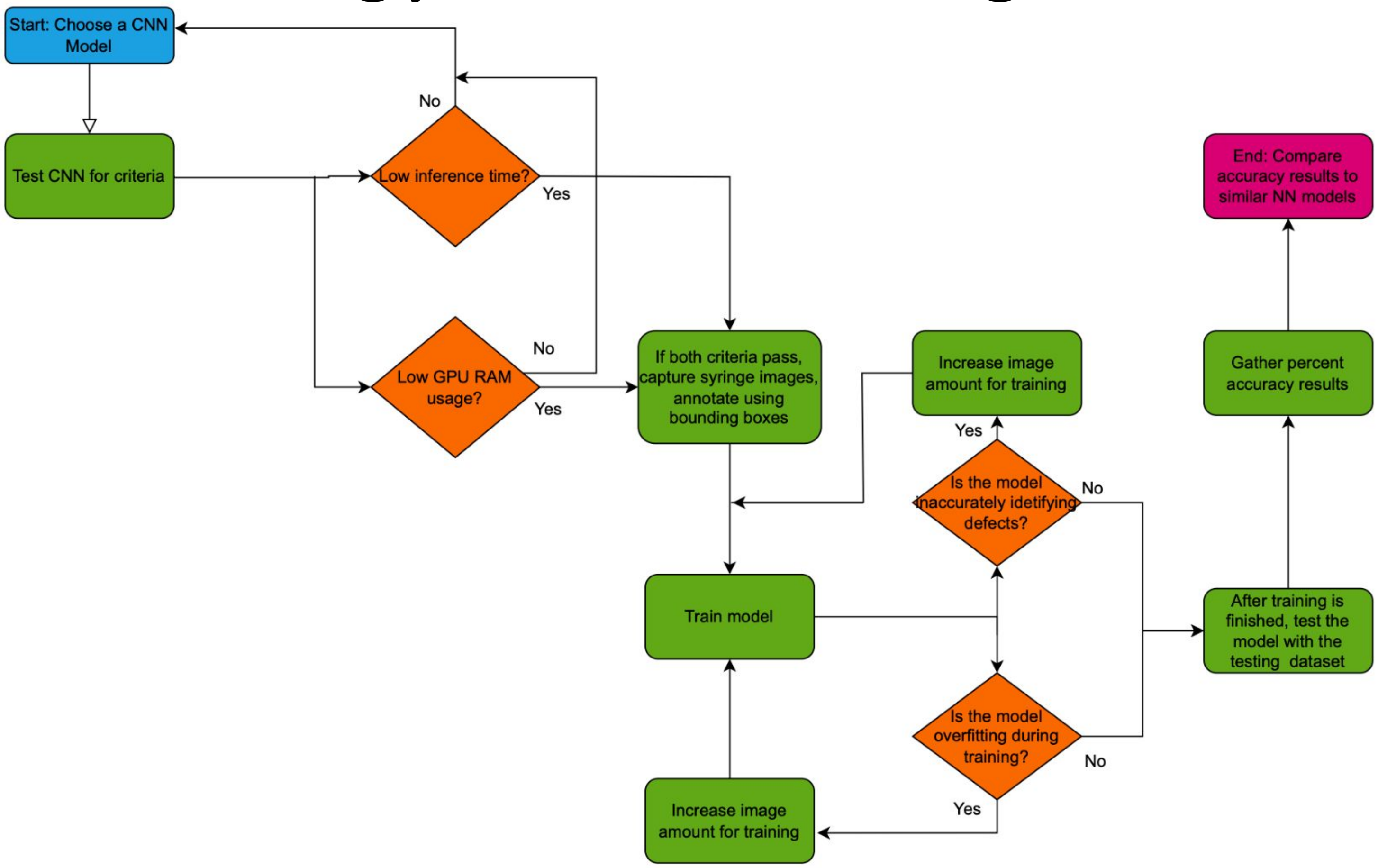


Figure 3: mAP score progression during training

Methodology: CNN Training Flowchart



Future Steps: Physical Setup

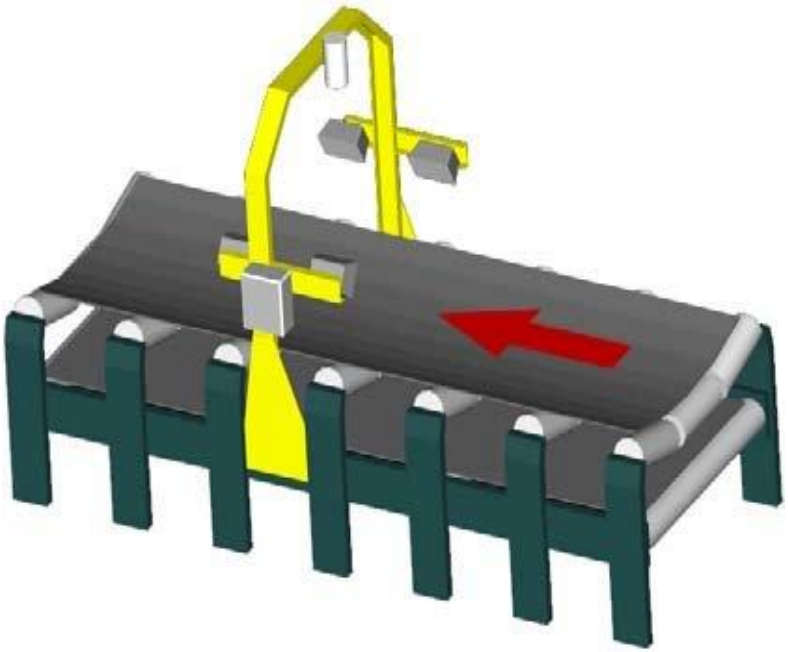


Figure 5: Example physical setup

https://www.researchgate.net/figure/Conveyor-belt-setup-with-camera-and-lights_fig3_228715797

- A physical simulation of the manufacturing process will be created, which contains a camera elevated above a conveyor belt.
- As syringes on the conveyor belt pass by a camera, it will take a top-view picture of the syringe and send it to the CNN to process for defects.
- The CNN will output a result containing the types of defects present on the syringe and indicate their locations on the image.

Engineering Decision Matrix: CNN models

Criteria	Weight	YOLO11	VGG-16	EfficientDet-D7x
Processing Time	10	8	7	5
GPU RAM Usage	7	9	9	9
Total		143	133	113

Materials

PyTorch

LabelImg

350x

References

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