Part 2: Reasoning-Based Questions

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Q1: Choosing the Right Approach

You are tasked with identifying whether a product is missing its label on an assembly line. The products are visually similar except for the label.

Q: Would you use classification, detection, or segmentation? Why? What would be your fallback if the first approach doesn't work?

A: I would use object detection because the main task here is to get the position of the label as the products are visually similar. Classification tasks are image based, like it would let me know if the entire image has a label or not, but detection can help me find the exact location of the label in the image. If detection doesn't work then I would use segmentation as my fallback as it does the similar task as detection and in addition we also get the masked label outline which could be helpful in some cases.

Q2: Debugging a Poorly Performing Model

You trained a model on 1000 images, but it performs poorly on new images from the factory.

Q: Design a small experiment or checklist to debug the issue. What would you test or visualize?

A: One of the reasons for the bad performance on new images could be poor training of the model on the dataset. So firstly, I will check the model metrics and figure out if there is any issue in my training process. If I don't find any such issue and the metrics are also in an acceptable range then I will check whether the new images are more or less similar in lighting, angles, etc factors to the images which were used for training. If that too is not the case then I would again fine-tune the model on the combined dataset including a set of these new images with the original dataset and consider a few more augmentation parameters to make the model more robust.

Q3: Accuracy vs Real Risk

Your model has 98% accuracy but still misses 1 out of 10 defective products.

Q: Is accuracy the right metric in this case? What would you look at instead and why?

A: No, accuracy is not the correct metric here, instead we should consider precision and recall. Precision tells us that out of all the positives predicted by model, how many were actually positives and recall tells us that out of all the actual positives that were there in the dataset, how many did the model predict correctly. So both of these metrics help us to get the exact picture of our model and we can also use F1 Score and confusion matrix to examine the model more in detail.

Q4: Annotation Edge Cases

You're labeling data, but many images contain blurry or partially visible objects.

Q: Should these be kept in the dataset? Why or why not? What trade-offs are you considering?

A: Yes we should have such images in the dataset because that helps to make the model more robust towards real world instances. In real world implementations, there can be cases when the object to be detected is captured partially, or the image captured is blurry and unclear, etc. If our model is already trained on such images then it can detect the object more effectively in such cases. Talking of the tradeoffs in this situation, very bad quality images can negatively impact the model training by misclassifying the labels, so very blurry images or images with background as the major portion should be avoided. This will help us have a robust model that can capture real world cases without compromising the accuracy of the model.