# Answers to the questions about the Utensil Classifier Machine

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**Q1. Strategies used**

The main strategies employed for a solid performance was mostly doing a lot of trial and error. Throughout the process it was important to make sure the machine was taking in information adequately. To do so, we just made a lot of test runs as we were doing the model. For example, testing certain images in the model even before it was finalized just to make sure bugs weren't present as we progressed by adding more classes to it. Another important aspect to developing the model was how we verified the dataset of images fed to it were clear and varied for every case scenario the model could encounter. Lastly, for the best output, the images have to be close to the machine for them to be properly detected and classified.

**Q2. Failures and reasons why**

One instance where the model failed was when it needed to detect tongs and potato peelers, two separate classes we added. When testing the model the images of tongs would be read as potato peelers. The main reason why it failed was because the classes themselves were mislabeled. The model was detecting the right images but the names were inverted which is why it was seen as a mistake. On another note, after some observations through testing, the model did slightly struggle when the cutlery was rounder at the edge. It takes more time for the model to class if the image fed to it is a spoon or fork. The main reason why this happens is because in most images all of them have a strong bright focal point and the machine likely uses that as a determining factor for each class.

**Q3. Difficulties and solutions**

As mentioned previously, the model had a lot of difficulty with cutlery that had a rounded or thicker finish. For instance, knifes were particularly challenging due to them having the pointiness of a fork but they also have the fill/thickness of a spoon. Consequently, the model struggled immensely trying to find the differences between the physicality of the knives and the two other utensils. To overcome the machine's confused state, the only thing that seemed to work was just feeding an unbelievable amount of spoons, forks and knives to the model. Each of those classes have a significant larger amount of examples compared to the tongs, peelers and no utensil classes. One more difficulty was how the model would detect any oval shaped object as a spoon. Even when not present the machine would read a spoon in the space. All in all, spoons and knives were the most problematic classes within this machine.

## **Q4. Performance and more classes**

Increasing the amount of classes wasn't a challenge for our model. The main challenge encountered was finding datasets of images of what we needed to feed the model. The performance wasn't hindered with more classes but the researching process was a bit more tedious. Ironically, the main difficulty with more classes is simply the time it takes for the model to read all the new information from all the new classes. Aside from that aspect, the only issue with more classes that arose was when the machine was introduced to tongs. In fact, previously forks had no recognition issues before the introductions of tongs but only started being slightly confused after the addition of the tongs class. Regardless of this minor confusion, the error between forks and tongs is minimal.

## **Q5. Surprises and takeaways**

The most surprising encounter while training the model was how easily it differentiated the tongs and potato peelers. Regardless of them being rather complex objects, the model learned both classes shockingly fast and was successful throughout the testing process as well. This particularly stood out because the easier shaped objects like knives, spoons and forks were a lot harder to train being a complete opposite to tongs and potato peelers. However the hatred for knives within this machine is terrible, which is hilarious.