Computer Vision Project

CMSC 307 - Artificial Intelligence Applications

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Reviewing AWS Rekognition Application

Figure 1: Navigating to the AWS Management Console

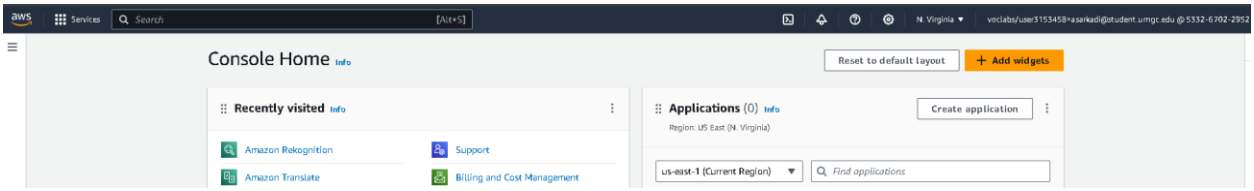


Figure 2: Search for the term ‘Rekognition’ to locate the Amazon Rekognition application.

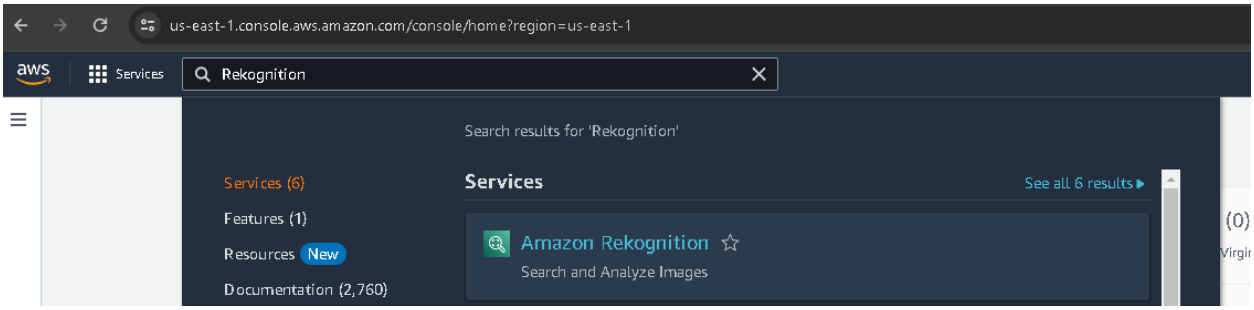


Figure 3: Once you are on the Amazon Rekognition page, you will be prompted with a demo, and several features in the left pane. Also, an overview is provided of how the application works, and how it does powerful analysis for identifying objects, people, and more. These features can be explored through the demo.

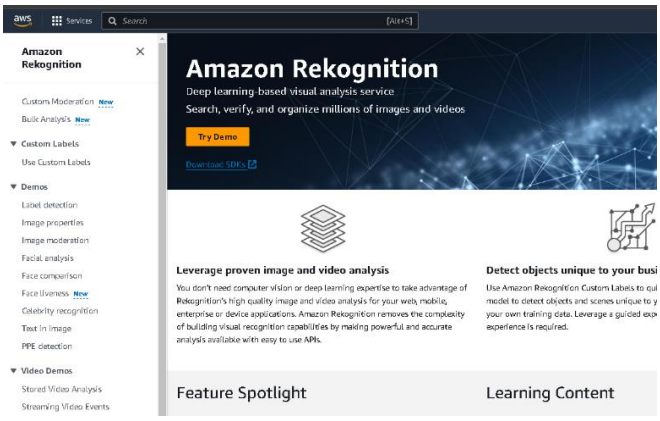


Figure 4: In this demonstration, choose ‘Label detection.’ In the left pane of the Amazon Rekogition page.

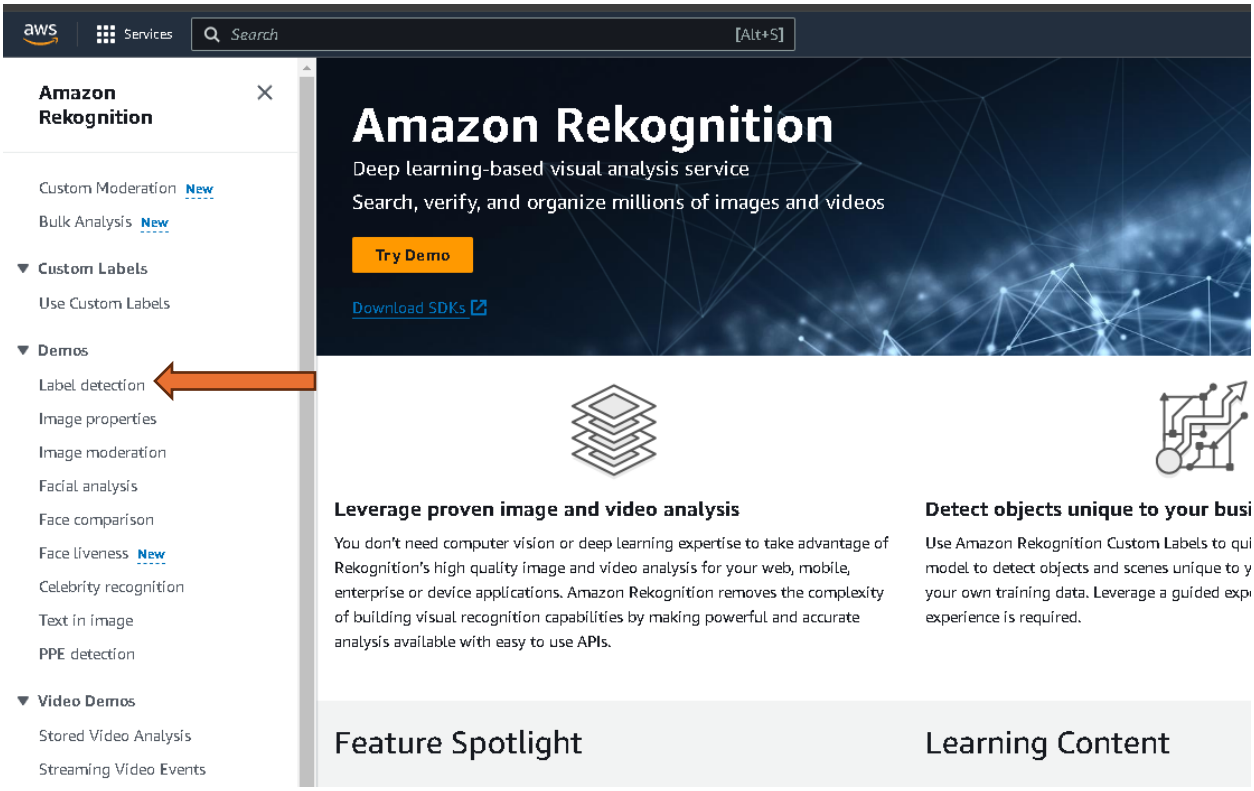


Figure 5: In Label detection, a sample image is used to show the capabilities of Label detection analysis within a photo and how it can be used for other images of your own.

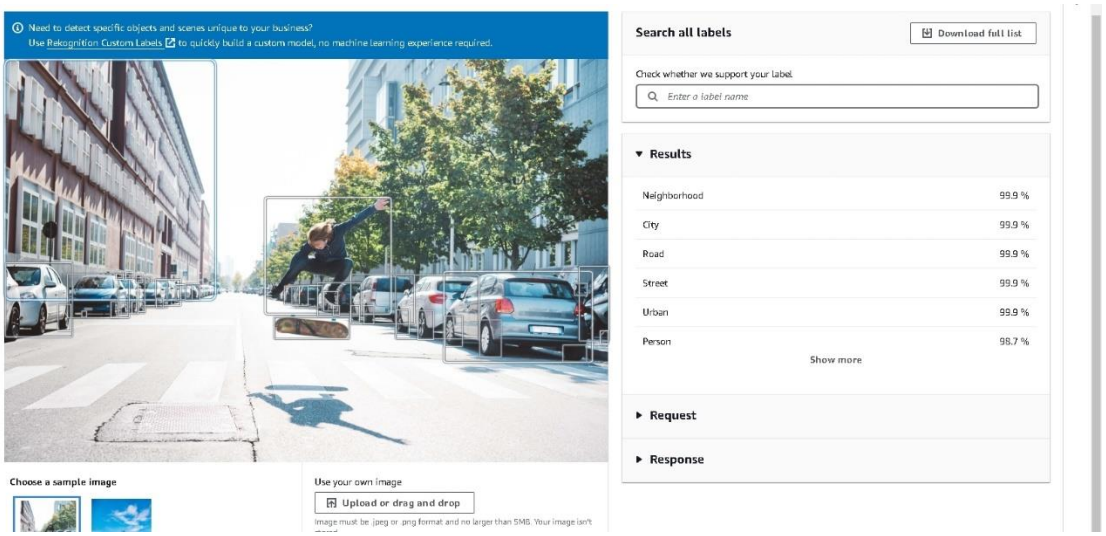
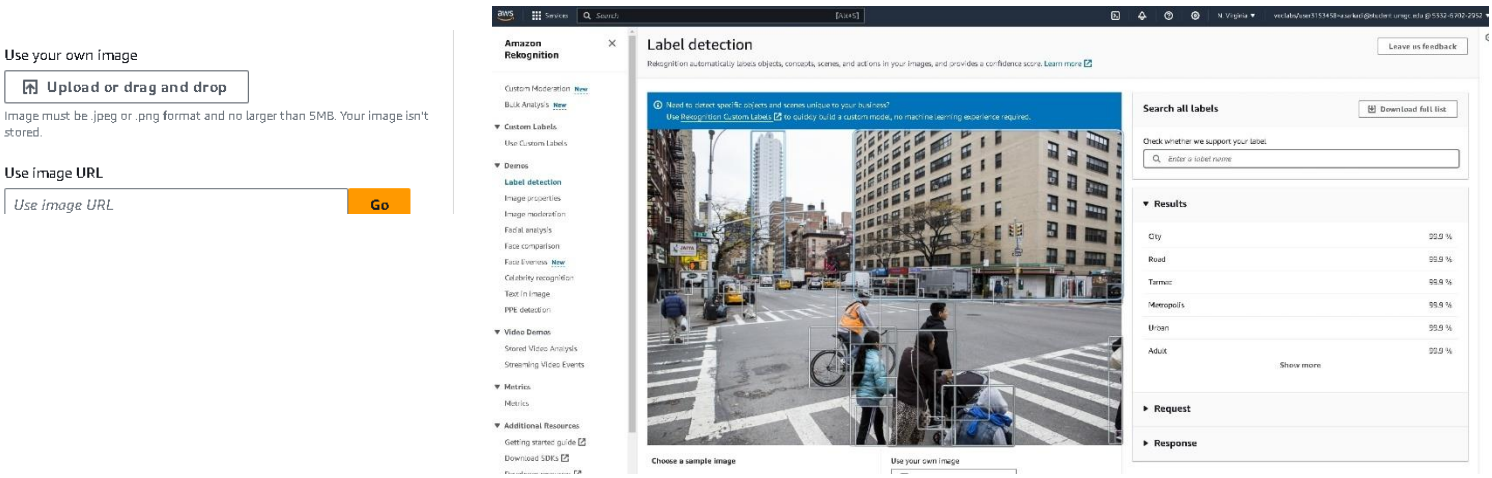


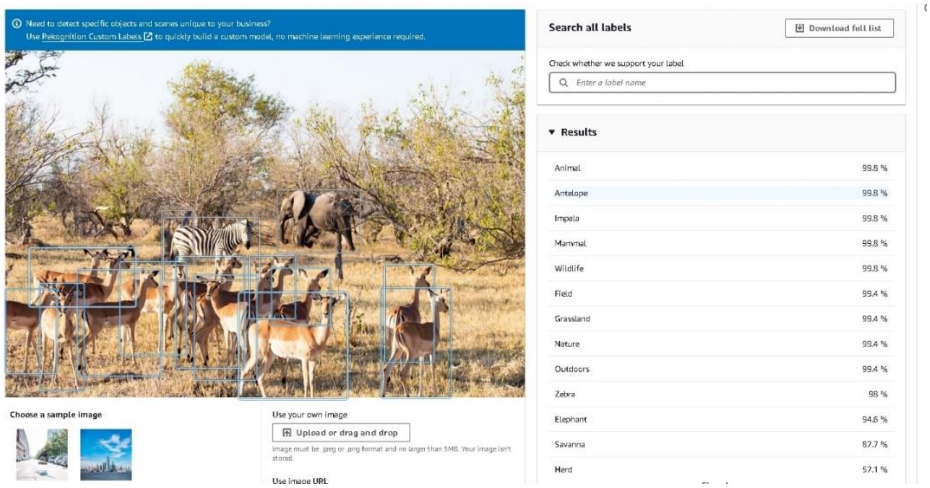
Figure 6 & 7: When using Label detection, there will be an option to upload your own image file for analysis and label detection. In this instance I chose a photo of a New York City Street from google images, saved it onto my computer, and uploaded it to the Label detection application.



In the figure above, I chose a New York City street with various amounts of objects to see how accurate Label detection was. When looking at all the labels, the detection was mostly successful, being able to identify various objects in the image chosen. Labels such as 'City', 'Urban', 'Metropolis' all received a 99.9% confidence. Furthermore, the application was also able to identify this has an intersection, labeling 'Zebra Crossing' at an 87.5% confidence percentage, and 'Intersection' at an 97.7% confidence percentage. It also identified traffic lights, and certain buildings. However, I did see some limitations that I expected to be analyzed properly. In the image above used for label detection, three trucks are included. Label detection was only able to detect one of the three trucks in the image. One of the trucks was also labeled as a car. Another issue I came across when analyzing the label detection was mislabeling or unable to label certain people, and objects. For example, the person carrying a plastic bag on the left intersection, the application labeled this as a 'handbag.' At first glance this isn't significant

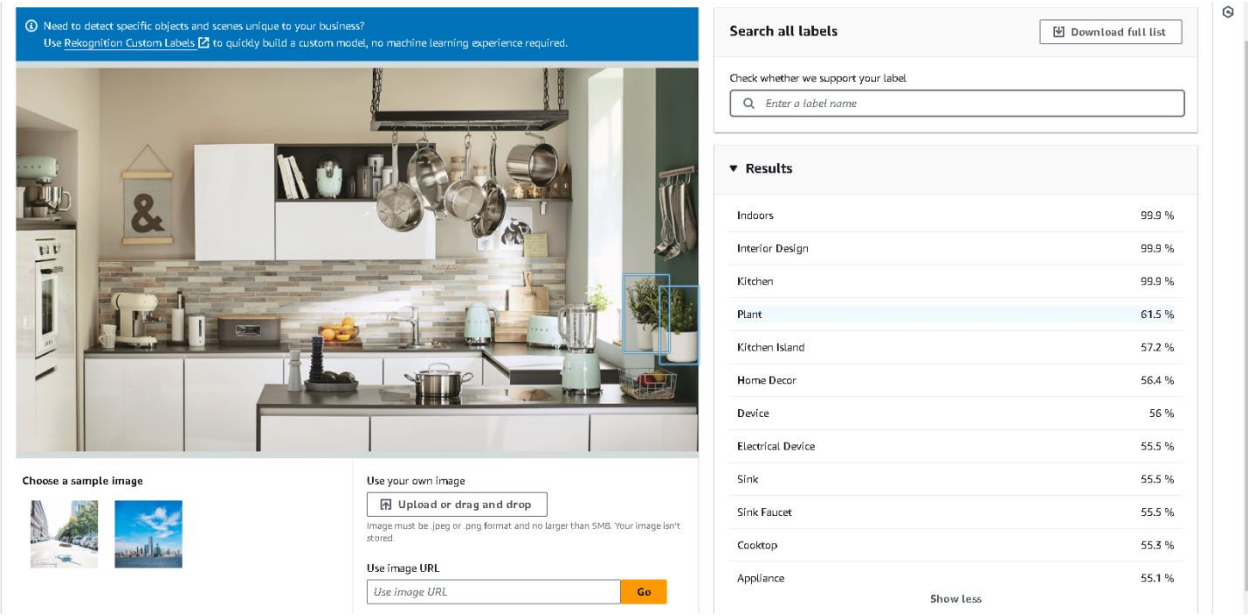
mislabeling, however, the stroller the women was carrying was also identified as a ‘handbag.’ This could have been due to the stroller not being in clear view in the image selected, the woman with the stroller is around many people. If the stroller was further down the intersection, separated from all individuals in the image, I believe the application would have been able to identify and label this as a stroller instead of a handbag. All the people in the photo were labeled as a ‘person’ or a ‘woman.’ What I found extremely strange in the label detection was that the person with the blue jacket and grey hoodie was labeled as a woman. Even though the person was facing the opposite direction of the camera when the photo was taken, and their face is completely covered. There is no significant evidence indicating that the person is a woman. Overall, I do see some limitations when using label identification. At first glance, I thought the application would be able to identify and label other objects in the image. Such as the fire escape stairs, the food cart, and street signs. However, all the labeling that was included was mostly correct at labeling objects and people, and the environment in which the image was taken.

Figure 8: An image of animals was saved and uploaded to Label identification for image labeling, and analysis.



In the figure 8, I wanted to choose a variety of animals in one image to see whether Label detection would identify the animals correctly, and the ecosystem they are in. Label detection was able to identify the zebra and elephant correctly. Giving the label 'Zebra' a confidence score of 98% and 'Elephant' 94.6%. I was surprised to see that 'Antelope' and 'Impala' were both given a 99.8% confidence score. When looking at the image after the label identification, I was unsure whether the animals were Antelopes, Impalas, or Gazelles. When doing research, I found that male impalas have horns, while female impalas do not. This is important to note because in the image I chose it included both male and female impalas. I found this very surprising because the label identification was accurate in identifying all animals within seconds. Others like myself who do not have a sophisticated knowledge of wildlife would have to do commit to research to correctly identify the animal. Label detection was also able to identify the ecosystem as a savanna, which is correct. However, it received a lower confidence score than expected (87.7%.) This could be due to the image receiving a 99.8% confidence score for 'Wildlife'. I expected both labels to have even confidence scores, I'm curious as to why trees weren't labeled specifically or ever mentioned. I ultimately believe this could be due to categorizing the trees into the 'nature' and 'wildlife' label. Giving 'Savanna' a lower confidence score. Overall, label identification did a thorough job at identifying the animals in the image uploaded, and correctly identifying the ecosystem in which the animals were in.

Figure 9: An image of a kitchen and its appliances to see whether label detection can identify this image as a kitchen, and label the kitchen appliances in the image uploaded, and label the environment the image was taken (indoors.)



This label detection analysis surprised me the most. I uploaded the image twice to make sure that the labeling and identification process did not miss any important labeling or content in the image. Label detection was able to identify this image as being indoors with a confidence percentage/score of 99.9%. Kitchen was also identified with a confidence score of 99.9%. There were only two objects that were labeled successfully (plants); however, they were given low confidence scores (61.5%.) Electrical devices were also given a low confidence score of 55.5%. Even though there are several electrical appliances in the image. Such as the blender, oven, toaster, and coffee machine. I'm surprised label detection was not confident in recognizing several objects in the image, the electrical appliances, kitchen appliances are all clearly visible, and the photo was in the highest resolution possible. Perhaps, all these objects fall under the 'device' and 'electrical device' label, however it still doesn't explain how the label confidence

score was very low. I expected the label identification service to at least identify some appliances in the photo besides the two plants. While ‘Indoors’ ‘Interior Design’ and ‘Kitchen’ all received a 99.9% confidence score, the rest of the labels have very low confidence scores ranging from 55.1% to 61.5%. Ultimately, label detection was able to identify the image as a kitchen, however several objects in the kitchen were given low confidence scores and weren’t properly labeled. When comparing this label detection to the other images used, there is not much insightful information that a person can interpret from this analysis. Nevertheless, I do believe that Label identification is a useful tool to help label and identify various images. Theoretically, I also believe that if I didn’t include the entire image, such as a partial image of the appliances, or objects I want the application to identify, it would do a better job at labeling and identifying these objects with higher confidence.

Figure 10: Using celebrity recognition service under the Amazon Rekognizition service. In the left pane, select ‘Celebrity detection.’ This will bring you to a page where you can upload various images of celebrities and the detection service will name the celebrity, and will give it a match confidence score.

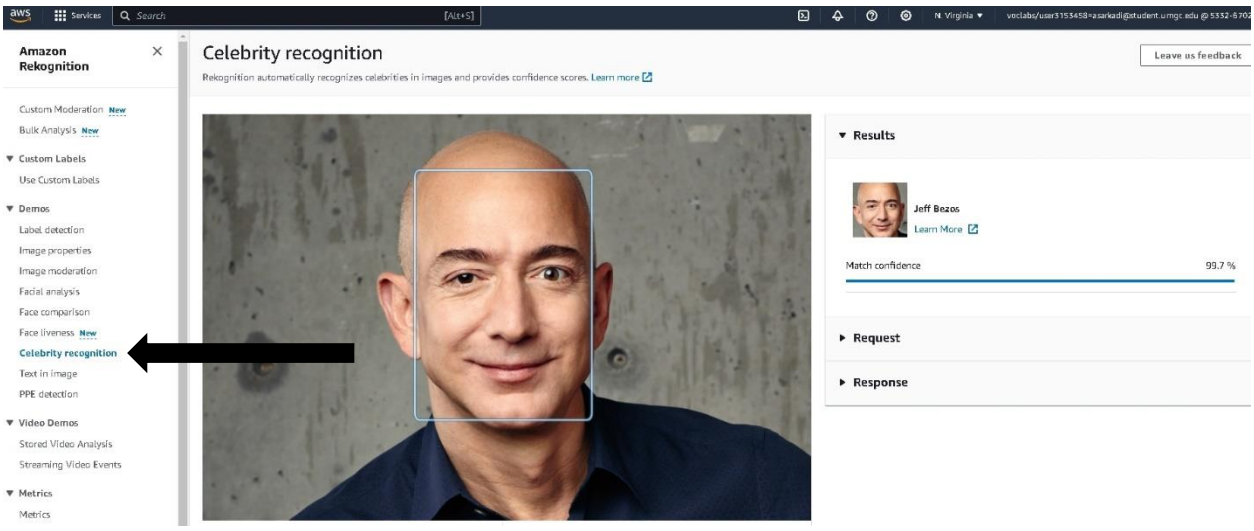
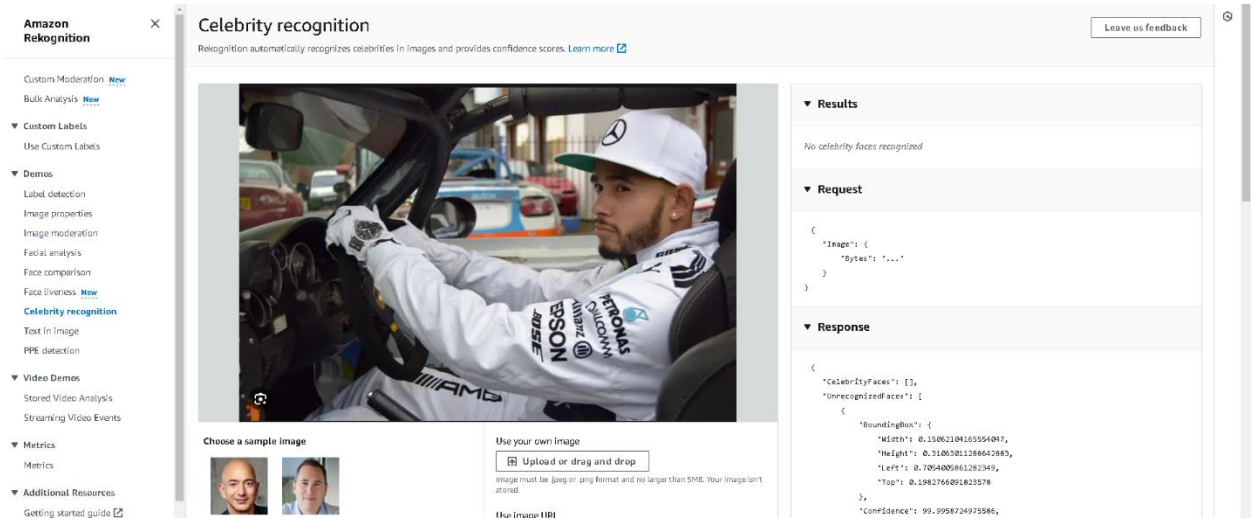
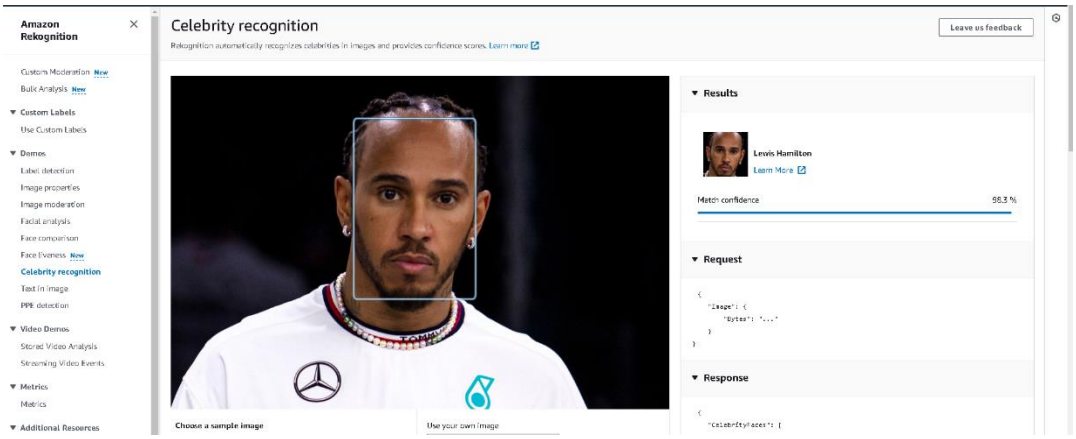


Figure 11: For the first image I chose a look alike of one of the current Formula 1 driver for Mercedes-AMG Petronas.



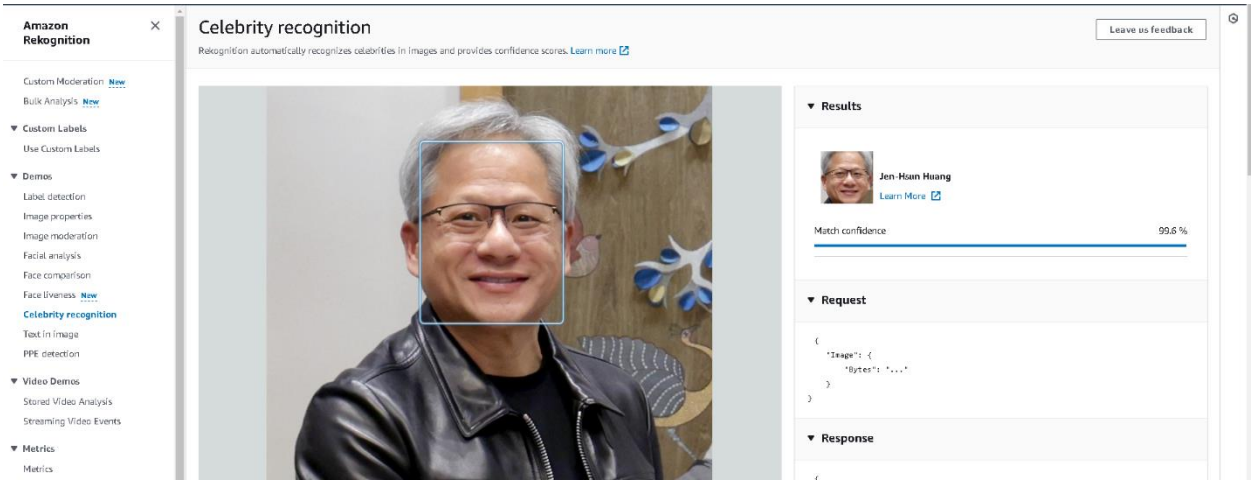
Despite the lookalike having Lewis Hamilton's racing suit, and being in a car, the celebrity recognition did not identify the person in the image as Lewis Hamilton. This is surprising to me because I tried to use the best image to replicate the celebrity.

Figure 12: The next image I chose was an actual photo of the Formula 1 driver, Lewis Hamilton, to see whether the celebrity identification was able to identify the celebrity.



Celebrity recognition was successfully able to identify the celebrity (Lewis Hamilton). The overall match confidence is 98.3%. I am surprised that the celebrity identification was able to differentiate for both images used. I assumed it would give this low confidence score of Lewis Hamilton, because I used an image with the lookalike in his driver suit, and in a car. Perhaps, if I used a higher resolution photo of a celebrity lookalike, the celebrity identification application would give a match confidence score and possibly misidentify the person in the image.

Figure 13: For the final celebrity identification analysis, I chose to use Jen-Hsun "Jensen" Huang, the current president of NVIDIA.



The celebrity recognition was successfully able to recognize the celebrity with a match confidence score of 99.6%. This did not surprise me; the image is a clear headshot of Jensen Huang. The photo was also taken from the first result in google images (Wikipedia) which I believed help identify the celebrity with a very high match confidence score.

When using the Amazon Rekognition service, I can see how the application can support a variety of industries in the future. One of which is public safety. I can see how Amazon Rekognition can be used to collect all the imagery from a reported crime and gather important image analysis for

an investigation. By giving confidence scores, labeling objects and people, this application can be fundamental towards public safety in areas with high crime rates. One research paper I explored looked at how Computer Vision can be used effectively for home cameras. The research paper used four different AI libraries (OpenCV, Keras, Numpy, and Pushbullet.) All of these tools were used to create a fully automative security system, sending an SMS message to the homeowner if an intrusion takes place. The official model of this project was called 'YOLO' standing for, 'You only look once.' (Kumar & Adithya, 2023.).

The conclusions drawn from the analysis evidently shows how Computer Vision technology can be used in instances where crime can be reported autonomously. A similar process can be used for the public. Cameras with these capabilities can allow police to potentially identify suspects by cross-referencing images and video with criminal databases and track the whereabouts of sed suspect. Another industry is quality control, Amazon Rekognition can be the perfect application for detecting inconsistencies for businesses that manufacture or ship items. One article I looked at discusses how Computer Vision based systems can be used to detect unfeasible, and useless items in the pharmaceutical industry, and how this model can be applied to other industries. Computer Vision technology can be used to check for inconsistencies in pills and capsules. Detecting and labeling scratches, crushed pills, and more. This model can be used within the Amazon Rekognition service in many other industries such as produce, (fruits, vegetables, meats, etc.), jewelry (gold, silver, diamonds, rare gems), beverages (water, soda, tea). Similar inconsistencies can be used in the industries I highlight. Employees within quality control can implement a data model to recognize any significant quality or health concerns for consumable products. Identifying these issues earlier with the use of computer vision will yield to better quality results and moral and ethical standards. All of these industries can benefit from the use of

Amazon Rekognition in the future, with its strong identification and labeling capabilities, industries can streamline quality control processes more efficiently, ensuring that customers are satisfied with the quality of products they purchase.

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