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ITAI 1378 September 25, 2025

Journal / Summary

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I walked into the machine learning workshop not quite sure what to expect, but I definitely didn't think I'd spend my time teaching a computer the difference between a chihuahua and a muffin. But that's exactly what we did, and it turned out to be a fun and surprisingly deep dive into artificial intelligence. The main goal was to build our own AI model that could look at the tricky "chihuahua or muffin?" pictures you see online and not get confused. Using Python tools like TensorFlow and Keras, we brought our model to life.

We were learning about image classification, This exercise thought me how to teach a computer to identify and label a picture. It's funny to think that for us, differentiating a dog from a snack is easy, but for a computer, both are just a jumble of numbers representing pixels. This is where Convolutional Neural Networks (CNNs) comes in, and they were a game-changer. I learned that they're kind of like an AI's version of a visual cortex. Instead of seeing the whole image at once, a CNN scans it in pieces, learning simple things like edges and colors first, and then using those to build up to more complex ideas like "snout" or "blueberry" in its deeper layers. This process lets it learn from the images directly, which makes it really effective for these kinds of task.

Perhaps the coolest and most significant trick we learned was transfer learning. Instead of trying to teach our AI model about vision from absolute scratch which would take a massive amount of data and time, we started with a pre-trained model. It's like hiring an expert who has already seen millions of random pictures and has a great general sense of shapes, textures, and objects. Our objective was to just give the computer, some specialized training on to differentiate chihuahuas from muffins. This shortcut was amazing. It meant we could get really impressive results quickly and without needing a supercomputer.

It wasn't all smooth sailing, though. I hit my first real snag just getting the data ready. Making sure every single image was sorted into the right "training" and "validation" folders felt a bit tedious, but I quickly learned that one tiny mistake in a file path could stop the whole process. Later, I had to watch out for overfitting. This is a classic trap where the model basically "memorizes" the training pictures instead of actually learning what a chihuahua or muffin *looks* like. It's like it aces the practice test but then fails the final exam because it can't handle new questions. To get around this, we used data augmentation—we showed the model slightly altered versions of our pictures, like flipped, rotated, or zoomed in. This forced it to learn the general features of a muffin or a dog, not just the specific pixels of the pictures we gave it.

This whole experience really opened my eyes. Now, when my phone automatically tags a friend in a photo, I have a much better idea of the incredible complexity happening behind the screen. It made AI feel less like magic and more like an understandable, and achievable, science. I also realized that building a model isn't a one-and-done deal; it's a creative process of tweaking parameters, testing the results, and trying again until you get it right.

After the workshop, my mind was racing with all the real-world possibilities. It's incredible to think that the same core ideas we used for a funny internet meme could be applied in serious ways. In medicine, these models could help doctors spot diseases in X-rays. In the car industry, they are essential for self-driving cars to tell a pedestrian from a lamppost. You could have drones checking farm crops for problems or even automated checkout lines at the grocery store. The applications feel almost endless.

Honestly, this was one of the most rewarding learning experiences I've had. It took these big, abstract concepts about AI and made them tangible. That moment when our model correctly identified its first new picture—that was a genuine "aha!" moment for me. It wasn't just code anymore; it felt like it was actually learning. The workshop has sparked a real curiosity in me to explore computer vision more, and it's given me the confidence to start dreaming up my own projects to tackle. It was the perfect mix of learning the 'why' and the 'how,' and I can't wait to see what I can build next.

References

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