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Chihuahua or Muffin Workshop with Convolutional Neural Networks – Reflection

In this week's lab experience, I was tasked to explore image classification using machine learning techniques. The images we were classifying fell into one of two groups, chihuahuas or muffins. This is the same data set as last week with the only difference being the type of neural network being used.

The dataset we are using for this week's assignment is still The Chihuahua vs Muffin dataset. This dataset consisted of 150 images divided between the two classes. We used this dataset to train and evaluate our Neural Network, which is a machine model inspired by the anatomy of the brain. It has interconnected layers of nodes or neurons that process and learn from data to perform classification or regression tasks. The neural network would try to classify an image whether it is a chihuahua or a muffin. Before the neural network model can classify images, a series of code was written to process it, convert it into a format that the model can understand. Also, the dataset having the images needed to be split into 2 halves serving different purposes (training and testing).

Now the major difference between last week's assignment and this week's assignment is the machine model we used. We used convolutional neural networks this week. Neural networks and convolutional neural networks are both architectures used in machine learning, particularly in the field of deep learning, but they serve different purposes and have distinct structures. Neural networks are flexible and can be used for many tasks, like sorting things into categories or predicting numbers. However, they are not the best choice for working with images. CNNs are made to work with data that has a grid shape, like images. They use special layers called convolutional layers that apply filters to the images, helping them find patterns and details. This is why the results are different! More on that later.

Now I have come to realize the most difficult part of any lab I work on is the coding that makes this experience happen. After loading the python tools and importing the data in JupyterLab, for the images to be analyzed, they need to be processed and prepared for analysis. These series of steps have a few lines of codes to function. The difficulty increases when it is time to train the model. When I look at codes, I like to "translate" to codes into English. If I can make it make sense in a sentence format, I can understand the concept. It is challenging to understand the codes for it. Thankfully, the codes have comments above to explain the purpose of the lines, which help me retain current information.

Some concepts I learned in this workshop are how neurons network function and converting the image data into tensors. As I said before, neural networks are models inspired by the human brain, they process and learn from data to perform tasks like classification or regression. A tensor is a multidimensional matrix, like an array. It is used to store and manipulate data efficiently. During the workshop, we must convert our images into a form the neural network model understands. A few simple and effective diagrams were shown that help reinforce the idea of how images are converted. Also, I learned how we train and test our model. So, the dataset is split into two: 80 percent is used to train the model to classify the images, and the remaining 20 percent is used to test the model. There was a total of 150 photos, the training set consisted of 65 chihuahua photos and 55 muffin photos, and the validation set consisted of 17 chihuahua photos and 13 muffins photos. In coding, the neural network model runs through the training dataset more than once so it can become more efficient in classifying images. Each run of the dataset is called an epoch, and, in this setting, it ran through the dataset ten times. Now the machine has not seen the other 20 percent of the dataset and it will be used for testing. I found this piece of information remarkably interesting because this is where we evaluate the performances of our machine learning models. Based on the report from the ten epochs, the average accuracy of the model was 85 percent, which indicates a compelling case of correctly classifying the images!

The techniques I learned in this workshop already have numerous potential real-world applications across various fields. For example, image classification algorithms can be utilized in healthcare to automatically identify diseases from medical imaging, enhancing diagnostic accuracy and efficiency. In the retail world, similar techniques can improve inventory management by classifying products through visual recognition, streamlining operations. Additionally, vehicles rely on advanced image classification to identify and differentiate objects on the road, ensuring safer travelling. Overall, the foundational skills I gained in this lab provide adequate space for developing innovative solutions that leverage machine learning in everyday life.

My favorite part of all the labs I have worked on is the output or results. After running the code showing the probability for each picture, I can see how the machine sees the images! I can even produce a conclusion, I have noticed when the color of fur of the chihuahua is similar to a fully baked golden brown muffin, the probability of the classification is downright 50/50! The machine did not struggle if the dog had any other color of coat, the probability of those images were above 90 percent of classifying it as a chihuahua. It is quite amusing when the machine is clearly wrong, mistaking a muffin for a chihuahua!

Thinking of how they can be used in the real world, convolutional neural networks are improving medical imaging by helping doctors find diseases more accurately in images like MRIs and CT scans. These models can spot tumors, fractures, and other issues, making it easier for healthcare professionals to diagnose patients quickly! By making image analysis faster and more reliable, they help improve patient care and efficiency in healthcare.

One thought that occurred to me is how they can be used in the wrong way. On the topic of medical imaging, what if the health care workers rely on the imaging heavily? To the point where it can lead to a diminished role for human expertise and critical thinking. When professionals depend too heavily on automated systems, they may overlook important insights or context that only a trained human can provide.

This experience has deepened my appreciation for the complexities of machine learning and the nuances involved in image classification. It is fascinating to see how seemingly simple tasks can challenge even advanced algorithms. I look forward to applying these techniques in future projects and exploring how I can enhance the model's performance further. Understanding these concepts will not only help my academic journey but also prepare me for real-world applications where precision is critical. Overall, this workshop has been a valuable and enjoyable learning experience.

References

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