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#### **Chihuahua or Muffin Workshop**

The "Chihuahua or Muffin" workshop was focused on applying image classification techniques using machine learning. The main goal was to teach us how to differentiate between two visually similar objects: Chihuahuas and muffins, using convolutional neural networks (CNNs). The workshop involved cloning a GitHub repository, loading the dataset, and then applying transfer learning to use an existing model to solve the classification problem. I also coded to view the images in the dataset. This made it easier to see how similar some of the images looked, which gave me a better understanding of why the model might struggle to classify them. By using transfer learning, we were able to speed up the training process, as the model already had some "knowledge" from being trained on other image datasets.

The workshop introduced several important concepts, particularly image classification and CNNs. Image classification is the process of identifying what category an image belongs to, such as whether an image is a Chihuahua or a muffin. CNNs were essential because they are designed to process visual data and detect patterns within images, making them effective for this kind of task. Transfer learning was another key concept. It involves taking a model that has already been trained on a large dataset and adjusting it for a new task, like our Chihuahua vs. muffin problem. This made the model more efficient since it didn’t need to start from scratch. I learned how helpful it can be in situations where you have limited data but still need accurate results. I used code to verify the predictions and could see how the model was improving.

One of the main challenges I faced was understanding how CNNs work, especially the various layers that contribute to image processing, like convolutional and pooling layers. Initially, I found it difficult to grasp how these layers work together to help the model recognize patterns. To overcome this, I went through the notebook multiple times and did some additional research online to better understand the role of each layer. Another challenge was dealing with the visual similarity between the Chihuahuas and muffins. Some images were almost identical in color and shape, making it hard for the model to classify them correctly. To address this, I experimented with data augmentation techniques like flipping and rotating the images. This increased the variety of training data and helped the model get better at distinguishing between the two classes.

The workshop gave me a clearer understanding of how machine learning models "see" images. Rather than recognizing objects like humans do, these models break down images into patterns and pixel values. It was interesting to see the model gradually improve as it processed more data, especially with the complex task of telling Chihuahuas and muffins apart. Transfer learning was one of the most useful techniques I learned. It allowed me to leverage a pre-trained model, saving time and computing power. I realized how valuable this approach can be in real-world situations where time and resources are limited.

There are several real-world applications of the techniques I learned. In healthcare, image classification models can help doctors identify conditions from medical scans, such as X-rays or MRIs. By using transfer learning, these models could quickly adapt to different types of medical images and improve diagnostic accuracy. Another potential application is in security systems. Image classification can be used for facial recognition or object detection in surveillance footage. By training CNNs on a specific dataset, these systems could automatically detect unusual activity or recognize specific people in real-time.

Overall, I found the workshop both challenging and rewarding. I appreciated the hands-on approach, especially the part where I used code to display and analyze the images. This helped me understand the difficulty of distinguishing between two similar-looking objects. It was also interesting to see how the model learned and improved with each iteration. I learned that patience is key when working with machine learning models. Training and adjusting the models takes time, and you have to be prepared for trial and error. Despite the initial difficulties, I found it satisfying to see the model improve with each tweak. The experience gave me a much better understanding of how machine learning can be used for image classification tasks.

In conclusion, this workshop provided a solid introduction to image classification using CNNs and transfer learning. This workshop not only gave me a deeper understanding of how CNNs work but also left me excited about the real-world applications of these techniques. Whether it’s classifying medical images, improving security systems, or even distinguishing between everyday objects like Chihuahuas and muffins, the possibilities for applying these skills seem endless. I now have a stronger foundation in these techniques, and I am excited to apply them to other projects in the future.

References

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