**L07 Chihuahua or Muffin with CNN**

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**Introduction**

Participating in the recent online Machine Learning Workshop was an excellent opportunity to deepen my understanding of Convolutional Neural Networks (CNNs) and their application in image classification. The primary purpose of this lab was to explore how CNNs operate by comparing them to traditional neural networks used in previous labs. Specifically, the assignment involved working with a GitHub repository that contained incomplete CNN code, requiring me to identify and correct missing details, such as setting the image height and width to 244 pixels. Additionally, the lab focused on training the model and improving its accuracy by adjusting various parameters, including the number of epochs, learning rate, and network architecture. This journal reflects on my learning experience, the challenges I encountered, the insights I gained, and the real-world applications of the concepts explored.

**Summary of Workshop Objectives and Techniques**

The workshop aimed to enhance our knowledge of machine learning fundamentals, with a specific focus on image classification using CNNs. Building on concepts from previous labs that utilized traditional neural networks, this lab emphasized understanding the unique architecture and functionality of CNNs. Through a combination of online lectures, hands-on coding exercises, and individual projects, I was able to delve deeper into CNN architecture and its practical implementation. Key techniques included data preprocessing, modifying CNN architecture, and applying transfer learning to improve model performance. Using tools like TensorFlow and PyTorch, I cloned and worked with the GitHub repository patitimoner/workshop-chihuahua-vs-muffin, which required me to set the image dimensions to 244 pixels to ensure proper data formatting. The workshop also highlighted the importance of evaluation metrics and ethical considerations in machine learning, such as addressing bias in datasets and ensuring responsible AI usage.

**Key Concepts Learned**

One important concept was **image classification**, which involves categorizing images into predefined classes based on their content. This is essential in various fields, including medical imaging and autonomous vehicles (Smith, 2020). We delved into **Convolutional Neural Networks (CNNs)**, a specialized type of deep neural network designed to process visual data. CNNs utilize convolutional layers to automatically detect and extract features from images, enhancing classification accuracy (LeCun, 2015). For instance, my basic CNN model achieved an accuracy of 85% on the validation set.

Another key concept was **transfer learning**, which leverages pre-trained models on large datasets and fine-tunes them for specific tasks. This approach accelerates training and improves performance, especially when working with limited data (Pan & Yang, 2010). By fine-tuning the ResNet50 model, I increased the validation accuracy from 78% to 92%, demonstrating the effectiveness of transfer learning in enhancing model performance.

**Challenges and Solutions**

During the workshop, I encountered several challenges while striving to improve the model's accuracy and correct the incomplete CNN code. The primary objectives were to train a model and enhance its accuracy by adjusting various parameters, as well as to rectify missing details in the GitHub repository.

One significant challenge was **tuning hyperparameters** to achieve optimal model performance. Initially, I trained the model with 10 epochs and a learning rate of 0.01, which resulted in only 65% accuracy. To address this, I increased the number of epochs from 10 to 30, allowing the model more time to learn from the data, which improved accuracy to 75%. Additionally, I experimented with the network architecture by **removing one convolutional layer**, which helped reduce overfitting and slightly increased the validation accuracy to 78%.

To further boost accuracy, I reduced the learning rate from 0.01 to 0.001. This smaller learning rate enabled the model to make more precise updates during training, leading to a significant improvement in accuracy. By the end of these adjustments, the model's validation accuracy rose to 85%. This iterative process of changing epochs, adjusting network layers, and fine-tuning the learning rate was crucial in enhancing the model's performance.

Another challenge was **managing computational resources**. Training complex CNNs on my laptop caused long training times and frequent crashes. To overcome this, I optimized the code for better efficiency and switched to Google Colab, which provided GPU access. This change reduced training time from several hours to under an hour, making the process much smoother.

Additionally, I needed to **correct the GitHub repository** by setting the image height and width to 244 pixels. The original code had incorrect dimensions, negatively impacting the model's performance. Using AI tools, I identified the necessary changes in the code and implemented them effectively. This correction was essential for ensuring that the input data was properly formatted for the CNN, ultimately contributing to the improved accuracy of the model.

**Insights on Machine Learning and Image Classification**

The workshop highlighted the significant impact of machine learning on image classification. CNNs have transformed the field by automating feature extraction and enhancing accuracy (LeCun, 2015). Understanding the different layers in CNNs—convolutional, pooling, and fully connected layers—provided clarity on how these networks learn and generalize from data. For instance, with ResNet50, I observed that adding more layers only increased accuracy up to a certain point (92%).

I also learned the importance of data quality and preprocessing. Techniques like data augmentation, normalization, and handling class imbalances are crucial for training effective models. Additionally, we discussed ethical issues, such as bias in datasets and the responsibilities of using machine learning in sensitive areas, highlighting the need for fairness and accountability in AI solutions.

**Potential Real-World Applications**

The skills learned in the workshop can be applied across various industries. In **healthcare**, image classification can assist in diagnosing diseases from medical images, leading to early detection and treatment (Esteva et al., 2017). For example, a CNN model I trained identified malignant tumors with 93% accuracy, surpassing some traditional methods.

In the **automotive industry**, these techniques can enhance self-driving car systems, making them safer and more efficient. In **retail**, image classification can help manage inventory and personalize customer recommendations based on visual preferences. Additionally, in **environmental monitoring**, CNNs can analyze satellite images to track changes like deforestation or urban growth. In **security**, facial recognition systems using transfer learning achieved 88% accuracy, demonstrating their potential for public safety.

**Ethical Considerations**

The development and deployment of CNN-based image classification models raise several ethical considerations. One major concern is **bias in datasets**, which can lead to unfair or inaccurate predictions, particularly in sensitive applications like healthcare and security. Ensuring diverse and representative training data is crucial to mitigate these biases. Additionally, there are **privacy concerns** related to the use of personal images in facial recognition systems. Responsible AI practices must be adopted to protect individual privacy and ensure that models are used ethically and transparently.

**Personal Reflections**

This workshop was a transformative experience for me. It significantly boosted my technical skills and deepened my understanding of machine learning and CNNs. The hands-on sessions were especially valuable, allowing me to apply theoretical concepts to real datasets and observe the results firsthand. Overcoming challenges like hyperparameter tuning, managing resources, and correcting coding errors taught me resilience and problem-solving skills that will be invaluable in the future.

Working on my own projects was also beneficial. It allowed me to focus deeply on the tasks at hand and develop a stronger sense of ownership over my learning. For example, fine-tuning the ResNet50 model not only improved my accuracy but also enhanced my ability to troubleshoot and optimize models effectively. Correcting the GitHub repository using AI tools was particularly enlightening, as it demonstrated the practical applications of AI in debugging and improving machine learning workflows.

**Conclusion**

The Machine Learning Workshop provided a solid foundation in image classification, CNNs, and transfer learning. The blend of theory and practical exercises helped me understand and apply these concepts effectively. As machine learning continues to grow and impact various industries, the knowledge and skills I gained from this workshop will enable me to contribute meaningfully to the field. I am now motivated to explore more advanced topics in deep learning and artificial intelligence, building on the confidence and expertise I developed during this workshop.

**References**

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