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Reflective Journal on Image Classification Using SVM and CIFAR-10

1. Reflection on Learning

1.1 Understanding SVM in Practice

Before this lab, I had a basic understanding of SVM, but using it for image classification with CIFAR-10 was eye-opening. I learned that while SVM isn't typically the go-to for image data, it can still perform decently with proper preprocessing. The idea of maximizing the margin between classes made me think about model generalization in a new way. I realized that simpler models like SVM can sometimes be as effective as more complex ones, depending on the task and dataset.

1.2 Data Preparation and Its Importance

Flattening the images and converting them to grayscale was interesting because it made me consider what data truly matters. By simplifying the images, I thought we might lose critical information, but the results showed that shape and texture (not color) are often enough for classification tasks like ours. This experience underscored how crucial it is to understand your data before diving into model selection.

1.3 Training and Model Performance

I expected SVM to struggle with images since it's not designed to handle spatial relationships like CNNs do. Surprisingly, it did better than I anticipated, especially with certain classes (like cats, dogs, and ships). This challenged my assumption that deep learning models are always the best option. However, SVM's limitations became clear when it came to handling complex visual data, reinforcing the importance of using the right model for the right problem.

1.4 Overcoming Challenges

Handling high-dimensional data was a challenge, but using a smaller subset and normalizing the data helped. This taught me about the trade-offs between data complexity and model performance. The lab helped me understand that preprocessing is just as important as the algorithm itself. Simplifying the data can make training faster, but it can also limit what the model can learn.

2. Applying What I Learned

2.1 Where Else SVM Fits

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Beyond image classification, I can see how SVM could be useful in other high-dimensional problems, like text classification or sentiment analysis. This lab made me appreciate the versatility of SVM for specific tasks, particularly when computational efficiency is a concern.

2.2 Relevance to Future Projects

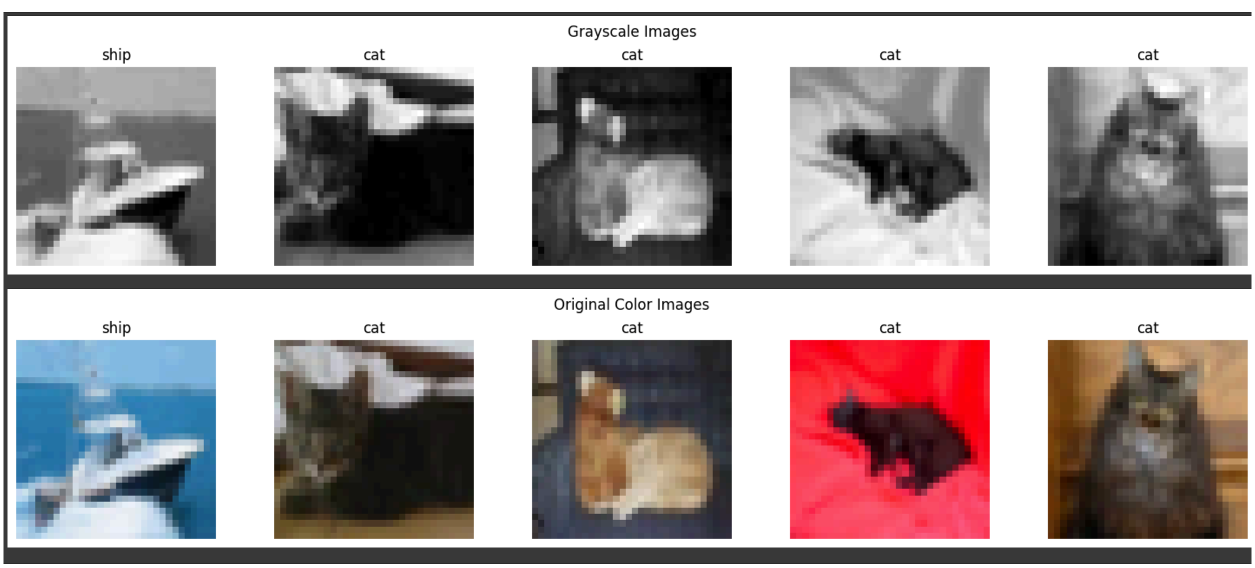
This experience will definitely influence how I approach future projects. I now realize it's important to match the algorithm to the problem at hand, rather than jumping straight to the most complex model. In future labs, I'll probably test simpler models like SVM early in the process to understand the data better before diving into deep learning techniques.

3. Key Takeaways

1. **Preprocessing Matters**: How you prepare your data has a significant impact on the outcome. Flattening and converting images to grayscale simplified the problem without losing too much important information.
2. **Not Every Task Needs Deep Learning**: While CNNs are better suited for image tasks, SVM can still perform well for simpler datasets or smaller subsets.
3. **Understanding Limitations**: SVM has strengths in handling high-dimensional data, but its limitations with images show that model choice is key depending on the problem.

4. Visuals

Grayscale vs. Color Images



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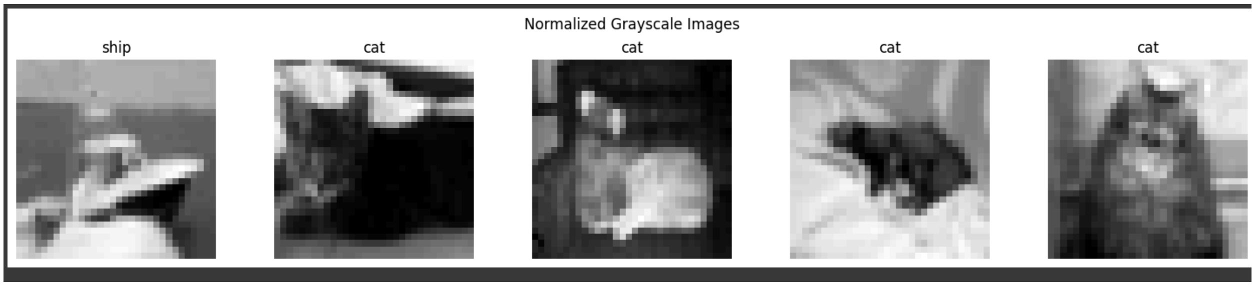

Conclusion

This lab showed me that SVM can still be a powerful tool in certain situations. It’s not always necessary to use deep learning—sometimes a simpler, well-applied model can do the job just as well. My biggest takeaway is the importance of thoughtful data preparation and critical model selection.