Neural Network: Image Analysis

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1 Abstract

This project is focused on image analysis by employing both Artificial Neural Networks(**ANN**) and Convolutional Neural Networks(**CNN**). Since neural networks can deal with complex patterns and visual image data, we developed image classification models for object recognition. Our approach involved pre-processing the images, developing the ANN and CNN models, training the model, testing the model, and finally evaluating the model to obtain the metrics such as accuracies respectively. This project demonstrates the ability of the neural network to accurately classify objects in classes; 'plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck', therefore contributing to the field of image analysis techniques that exist out there in tech fields.

2 Introduction

In the ever-evolving field of Image analysis, Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) have proven to be vital models. Our goal is to compare the performance of these models for precise object recognition leveraging the CIFAR-10 dataset—comprising a diverse array of images across multiple classes and identifying the nuanced differences between the approaches adopted by these models. By exploring the complex layers of neural networks, using diverse activation functions, epochs, and an in-depth analysis of test and train performances we also seek to understand the nature, strength, and limitations of each model. Through thorough comparison and exploration, we aspire to shed light on the details of ANN and CNN models in the context of image classification, contributing valuable insights to the field of computer image vision and paving the way for more informed model selections in practical applications.

3 Related Work

The age of Image classification and recognition using neural networks has steered the extensive studies in literature, for instance, various studies have investigated the importance of different neural network architectures, particularly Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), in addressing the complexities of image analysis.

In the study by LeCun et al. (1989).Backpropagation Applied to Handwritten Zip Code Recognition. The ability of learning networks to generalize can be greatly enhanced by providing constraints from the task domain. This paper demonstrates how such constraints can be integrated into a backpropagation network through the architecture of the network. This approach has been successfully applied to the recognition of handwritten zip code digits provided by the U.S. Postal Service.

Additionally, Simonyan and Zisserman (2015)-Very Deep Convolutional Networks for Large-Scale Image Recognition, explored the depths of CNN architectures, introducing deeper networks such as VGGNet, which demonstrated the improved performance on various image datasets by leveraging increased network depth.

Moreover, a recent study by Zhang et al. (2021)- "A Study on Different Functionalities and Performances among Different Activation Functions across Different ANNs for Image Classification", has investigated the specific strengths and weaknesses of ANNs and CNNs in image classification tasks across diverse datasets. In this paper, CNN displayed remarkable results in image recognition compared to ANN. However, ANN has also demonstrated some reliability in certain contraints.

Conclusively, despite the rich and extensive studies about the performance of the two models, there is always ongoing research, studies and debates on the best scenario for application of the models in image classification cases. Our study is also aimed to contribute to this bank of knowledge through a comprehensive comparison of these models on the CIFAR-10 dataset, shedding further light on their performance, strengths, and limitations in a practical image recognition setting.

4 Dataset Overview

The CIFAR-10 dataset is a data package used for image classification, consisting of 60,000 32x32 color images distributed across ten classes where each class contains 6,000 images. It is an ideal dataset for training and evaluating machine learning models aimed at image classification tasks.

The dataset is categorized into the following classes: 'plane,' 'car,' 'bird,' 'cat,' 'deer,' 'dog,' 'frog,' 'horse,' 'ship,' and 'truck.' Notably, the dataset's structure includes 50,000 training images across five batches and 10,000 test images within a separate batch. The test batch is derived of precisely 1,000 randomly selected images from each class, ensuring a uniform representation for evaluation purposes.

The training batches have a balance of 5,000 images per class, individual batches might vary in their distribution of images across classes due to randomization. The dataset ensures each image is exclusively assigned to one of the ten predefined classes. Notably, the 'automobile' class is made up of sedans, SUVs, and similar vehicles, while the 'truck' class is exclusively derived of larger trucks, distinct from pickup trucks.

5 Proposed Approach

We implemented two neural network models to experiment with this dataset to compare accuracies: Artificial Neural Network (ANN) and Convolutional Neural Network (CNN). We used both models to classify the dataset and took the overall accuracy, as well as split up the accuracy for each class in the dataset to measure where each model excelled and struggled. Additionally, we plotted the loss curves throughout the iterations during the training of the models.

6 Results and CNN Model Accuracy

The evaluation of the Convolutional Neural Network (CNN) model on the CIFAR-10 test dataset generated insightful results and was relatively successful in its performance of classifying various image categories.

The overall accuracy of the CNN model on the 10,000 test images was calculated to be 61%, indicating its proficiency in correctly identifying the image classes within the CIFAR-10 dataset.

6.1 Classification Accuracy

The model's performance was further assessed on a class-by-class basis, revealing varying degrees of accuracy across different categories:

The above table shows the accuracy of the model for each classification. Notably, the model achieved higher accuracies for classes such as 'Car' (76.7%), 'Ship' (77.7%), and 'Truck' (69.3%), indicating a stronger capability in accurately identifying these image classes. Oppositely, classes like 'Cat' (46.7%) and 'Deer' (51.7%) exhibited lower accuracies, suggesting relatively more challenges in correctly classifying between various animals as compared to distinct objects or vehicles.

Table 1: CNN Classification Performance

Class	Accuracy (%)
Plane	68.0
Car	76.7
Bird	55.2
Cat	46.7
Deer	51.7
Dog	52.7
Frog	58.9
Horse	61.3
Ship	77.7
Truck	69.3

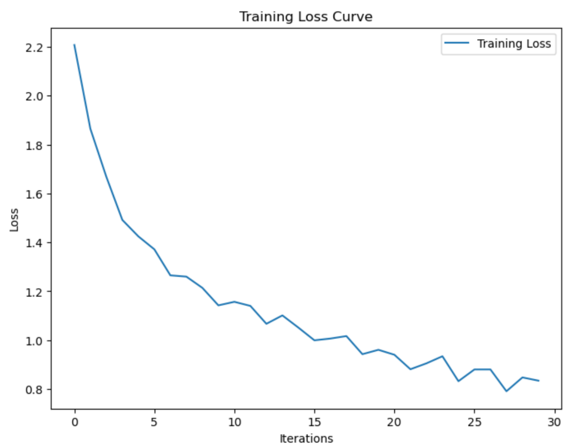

Figure 1: CNN Loss

6.2 Training Loss

During the training process, the model experienced a consistent decrease in loss over epochs, indicating a progressive improvement in learning. The decreasing trend in the loss curve signifies the model's enhanced ability to fit the training data, a significant aspect contributing to the achieved accuracies.

6.3 Analysis

The observed difference in accuracies among various classes displays the model's proficiency in identifying image categories within the CIFAR-10 dataset. Factors such as image complexity, distinct visual features, or the abundance of training samples might influence the model's performance across various classes.

While the overall accuracy of 61% portrays a commendable performance on the entire test dataset, future model enhancements could focus on improving accuracy for the animal classes with relatively lower success rates. Fine-tuning the model architecture, adjusting parameters, or incorporating additional data augmentation techniques might aid in enhancing the model's performance across all classes.

7 Results and ANN Model Accuracy

Below are the results for the Artificial Neural Network (ANN) on the CIFAR-10 dataset. Overall, ANN had much worse accuracies for each class compared to CNN, which was expected as convolutional networks are known for being more accurate with image processing. The total accuracy for ANN across all classes was 51%.

Table 2: ANN Classification Performance

Class	Accuracy (%)
Plane	56.0
Car	63.3
Bird	37.0
Cat	39.0
Deer	34.0
Dog	40.5
Frog	58.1
Horse	61.1
Ship	66.1
Truck	63.7

Overall, the trend for differences in accuracies across the classes for ANN matched that of CNN. With classes like 'Truck' (63.7%), 'Ship' (66.1%), and 'Car' (63.3%), the accuracy was much higher compared to animal classes like 'Cat' (39.0%), 'Dog' (40.5%), and 'Deer' (34.0%).

7.1 Training Loss

Above is the data for the training loss on ANN. Note that like CNN, there is a downtrend in loss as the number of iterations increases. However, the rate of change for the loss curve for CNN was much higher. Not only was there a much sharper decrease in loss by the 5 iteration mark, the final loss for CNN was 0.4 lower.

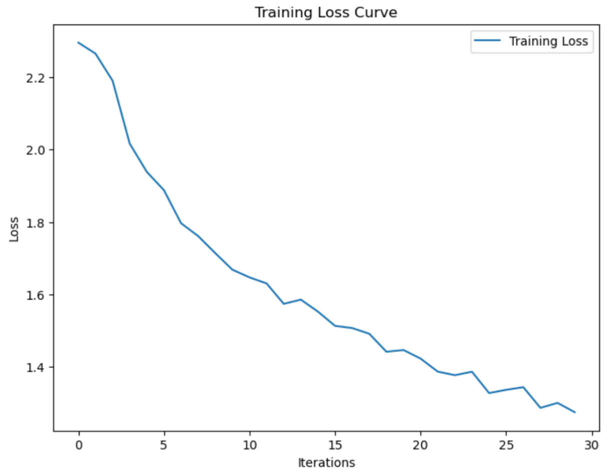

Figure 2: ANN Loss

7.2 Analysis

With an overall accuracy of 51%, Artificial Neural Networks don't seem to be well suited for this type of dataset. In an attempt to raise the accuracy, we also tried to transform the data using the built-in functions from the torchvision class. However, this did not yield a higher accuracy so it was not included in our final code. We could have tried a different optimization function, but we believe stochastic gradient descent was the appropriate option for this experiment. We experimented with the Adam optimization function instead of SGD but this also yielded a lower accuracy.

8 Discussion and Conclusion

After comparing both models, the Convolutional Neural Network was clearly better suited for this dataset type. As previously mentioned, CNNs are much better at processing spatial relationships, making them a clear choice for image classification. The 10% overall difference in accuracy clearly indicates that CNN is more powerful for this type of data. Tweaking parameters, the model's architectures, or preprocessing the data in a different manner may be able to increase the accuracy of either model which could be the direction for further experimentation in this area.

9 Statement of Contributions

Grant Westerholm, Yvonne Itangishaka, Melissa Pinto - ANN

Torin Borton-McCallum, Riley Adams - CNN

Validation - All

Write up - All

10 References

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