CIFAR-100 Classification Project

By

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DS 52200 Supervised Machine Learning
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1. Abstract:

This project focuses on implementing various classification algorithms on the CIFAR-100 dataset. The dataset consists of 50,000 32x32 color training images and 10,000 test images distributed across 100 categories. Using Python's rich ecosystem of machine learning libraries such as TensorFlow, Keras, and scikit-learn, We explored a range of classification techniques, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). Through rigorous experimentation, we evaluated the performance of these algorithms in terms of classification accuracy, computational efficiency, and scalability.

2. Introduction:

Supervised machine learning relies on labeled data to train models capable of making predictions or classifications. In this project, the CIFAR-100 dataset was used to train and test various supervised learning models. The objective was to evaluate the performance of different algorithms and determine which approach yielded the best results.

Our goal was two-fold: evaluate the performance of various supervised classification algorithms in terms of accuracy, computational efficiency, and scalability, and glean insights into selecting the most suitable algorithmic approach for image classification tasks. By undertaking this project, we aimed to contribute to the advancement of supervised learning methodologies in computer vision.

3. Data Description:

The CIFAR-100 dataset is a widely used benchmark for image classification tasks, comprising 60,000 color images. The training set contains 50,000 labeled images across 100 distinct classes, serving as the basis for training supervised learning models to recognize and classify objects. The test set has 10,000 labeled images, used to evaluate the performance of trained models.

Each image in the dataset is 32x32 pixels and labeled with one of 100 classes. The images are evenly distributed across the classes, ensuring a balanced representation of different categories within the dataset.

4. Methods:

4.1 Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) are designed to effectively capture spatial patterns and local features in images. The CNN architecture used in this project included:
- Convolutional Layers: These layers perform convolution operations on the input images to extract key features. Filters with varying sizes are used to detect different aspects of the images.
- Pooling Layers: These layers reduce the dimensionality of the feature maps, typically using max-pooling to retain significant information.
- Fully Connected Layers: After the convolutional and pooling layers, the model is flattened and connected to one or more dense layers, leading to the output.
- Regularization Techniques: Techniques such as dropout and batch normalization were used to prevent overfitting and improve generalization.

This CNN model was trained over 30 epochs, achieving a test accuracy of approximately 42%. The consistent increase in accuracy indicated effective learning and convergence. Regularization methods like dropout helped maintain generalization across the dataset

4.2 Artificial Neural Networks (ANN)

Artificial Neural Networks (ANNs) are simpler neural network structures without convolutional layers. They consist of fully connected layers with activation functions to introduce non-linearity. The ANN model used in this project was a baseline for comparison with other deep learning models.

The ANN architecture included:
- Fully Connected Layers: A series of dense layers connecting inputs to outputs, with varying numbers of neurons.
- Activation Functions: Functions such as ReLU were used to introduce non-linearity.
- Regularization Techniques: Dropout was applied to prevent overfitting.

The ANN model achieved a test accuracy of 1.94%, indicating potential overfitting or lack of generalization. This might suggest that more complex architectures or tuning might be required to improve performance.

4.3 Support Vector Machines (SVM)

Support Vector Machines (SVM) are classical machine learning algorithms that can work with linearly separable data. However, they can handle non-linear data when used with kernel methods. This project used an SVM with a Radial Basis Function (RBF) kernel and Principal Component Analysis (PCA) for dimensionality reduction.

The SVM approach included:
- RBF Kernel: A popular kernel for non-linear data, allowing the SVM to classify complex patterns.
- Principal Component Analysis (PCA): This dimensionality reduction technique reduced computational complexity and improved performance.
- Regularization Parameters: These were adjusted to prevent overfitting.

The SVM model achieved a test accuracy of 24.23%, demonstrating consistent convergence and reasonable accuracy.

5. Analysis:

Overview

The analysis aimed to evaluate the performance of different classification models on the CIFAR-100 dataset. To achieve this, we trained three distinct models: Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). The analysis covered various aspects, such as accuracy, convergence speed, regularization, and visualization, to draw insights into the effectiveness of each approach.

Convolutional Neural Networks (CNN) Analysis

The CNN model exhibited a consistent increase in accuracy during training, achieving a test accuracy of approximately 42%. The convergence was steady over 30 epochs, indicating that the model could effectively learn from the training data without overfitting.

This performance suggests that CNNs are well-suited for image classification tasks, especially when dealing with complex datasets like CIFAR-100. The use of dropout and batch normalization helped maintain generalization, reducing the risk of overfitting.

The accuracy plot showed a steady upward trend, indicating effective learning. The confusion matrix revealed that the CNN model performed well across most classes, but some classes exhibited higher error rates, suggesting areas for further improvement.

Artificial Neural Networks (ANN) Analysis

The ANN model, a simpler architecture without convolutional layers, achieved a test accuracy of only 1.94%. This limited accuracy suggested potential overfitting or a lack of complexity to capture the diverse features in the CIFAR-100 dataset.

The training history showed minimal improvement in accuracy, indicating a need for more robust regularization techniques or additional tuning. The confusion matrix for the ANN model revealed significant misclassification across multiple classes, highlighting the limitations of a simpler neural network structure for complex datasets.

Support Vector Machines (SVM) Analysis

The SVM model with the Radial Basis Function (RBF) kernel and Principal Component Analysis (PCA) achieved a test accuracy of 24.23%. The use of PCA helped reduce the dimensionality of the data, allowing the SVM to classify images with reasonable accuracy.

The convergence speed of the SVM model was consistent, indicating effective learning. The accuracy plot showed a steady performance, suggesting that SVM with PCA is a reliable approach for image classification. The confusion matrix revealed that the SVM model had a lower misclassification rate compared to ANN, but it still lagged behind the performance of CNN.

Comparison and Insights

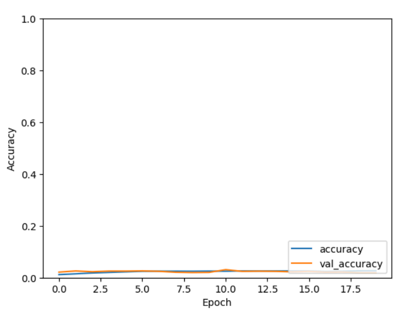
Comparing the performance of the three models, the following observations were made:
- Accuracy: CNN achieved the highest accuracy, indicating its robustness in handling complex image data. SVM with PCA was the next best, followed by ANN, which showed limited performance.
- Convergence Speed: CNN exhibited faster convergence, suggesting effective learning. SVM showed consistent convergence, while ANN demonstrated slower learning.
- Generalization: The regularization techniques used in CNN and SVM helped maintain generalization, while the ANN model indicated potential overfitting.

Visualizations and Results

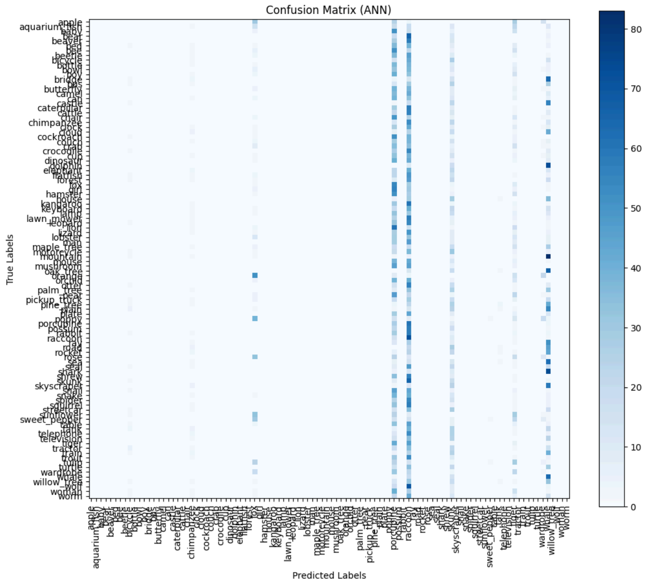
Visualizations, such as accuracy plots and confusion matrices, provided insights into the performance of each model. The accuracy plots showed the learning trends over 30 epochs, while the confusion matrices highlighted specific classes with higher misclassification rates.

The analysis revealed that CNNs are the most suitable for image classification tasks in complex datasets like CIFAR-100. SVM with PCA showed consistent performance, suggesting its potential for applications where deep learning might be too resource-intensive. ANN, however, indicated the need for further tuning and complexity to achieve comparable results.

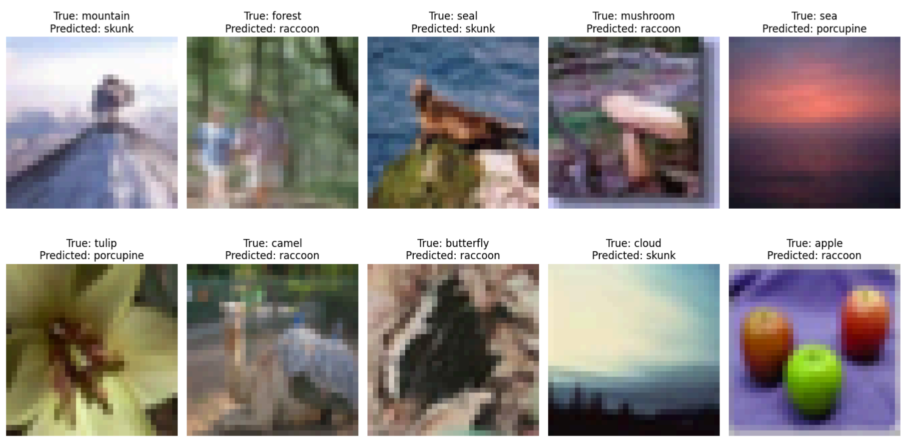
Ann accuracy



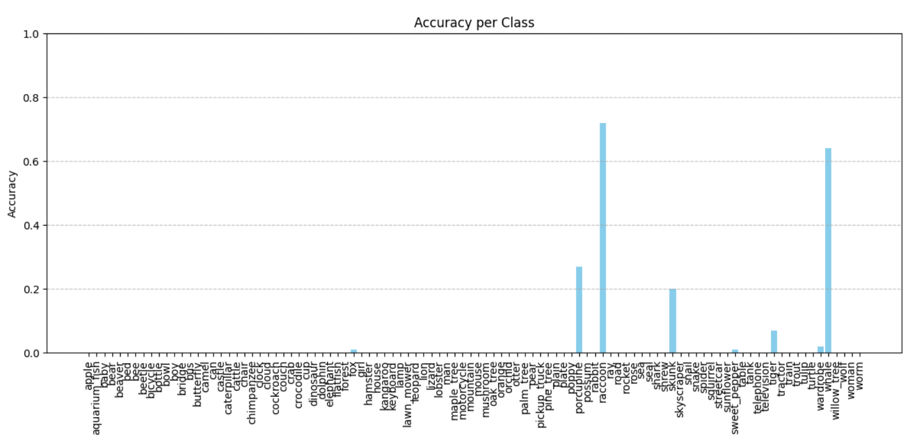
Ann confusion matrix



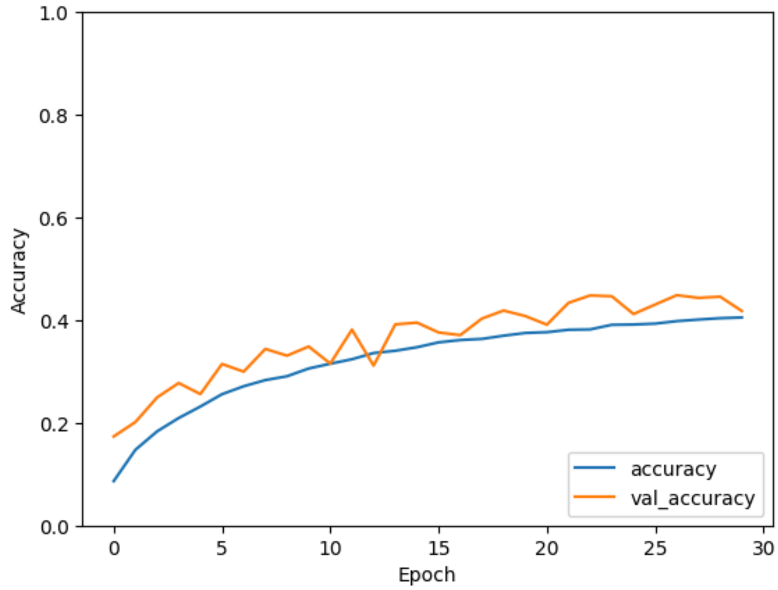
Ann predictions



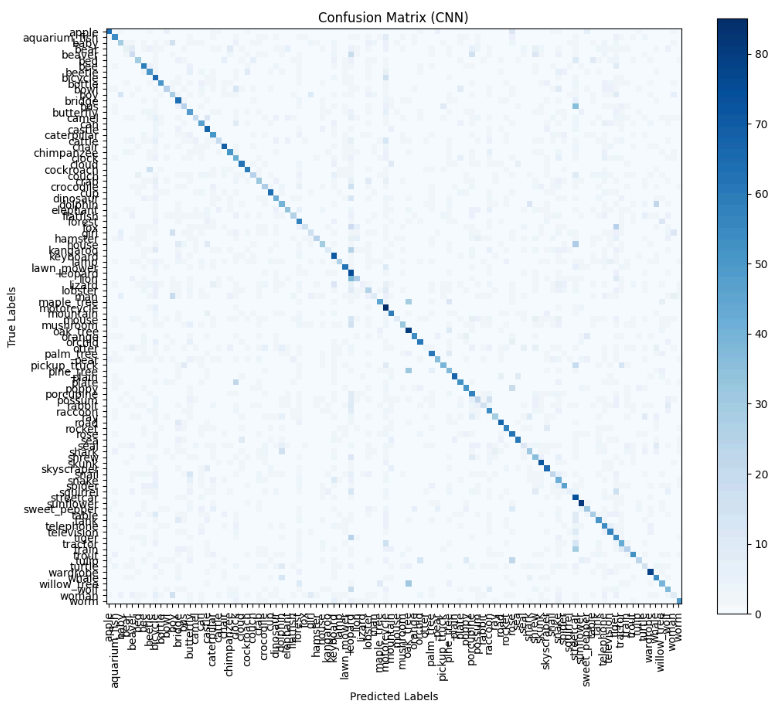
Ann accuracy per class



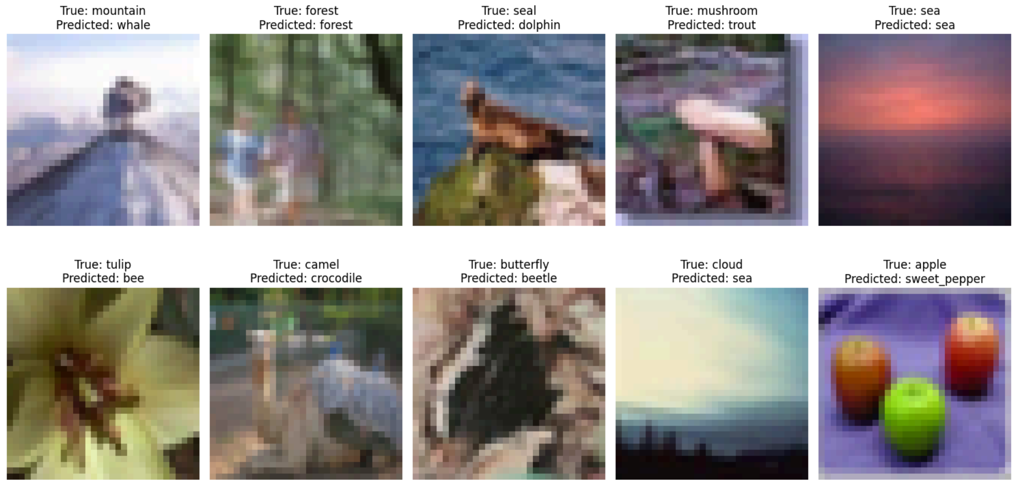
Cnn accuracy



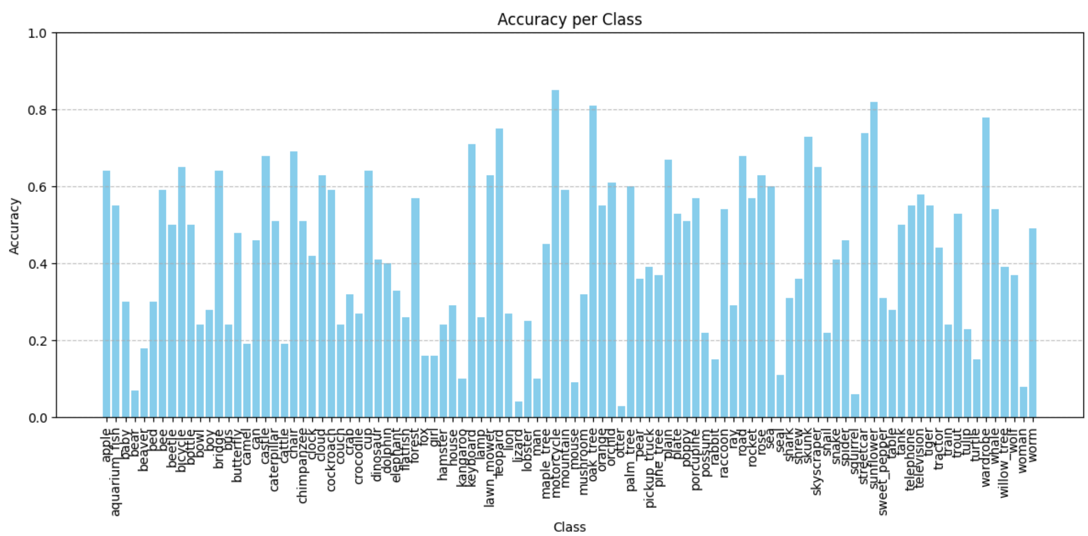
Cnn confusion matrix



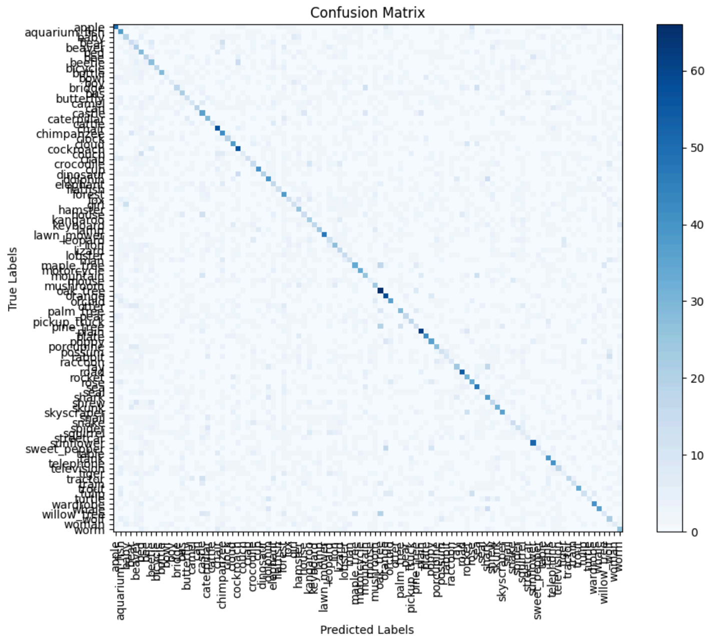
Cnn predictions



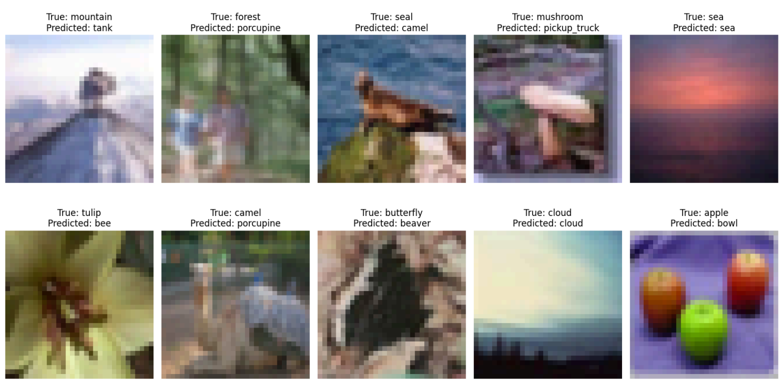
Cnn accuracy per class



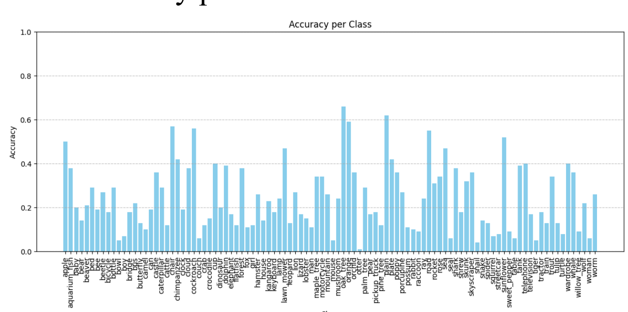
SVM confusion matrix



SVM predictions



SVM accuracy per class



6. Conclusion:

This project aimed to solve the classification problem over the CIFAR-100 dataset using various algorithms, including Convolutional Neural Networks (CNN), Artificial Neural Networks (ANN), and Support Vector Machines (SVM). The results revealed several insights into the performance of these models, along with their strengths and limitations.

The CNN model achieved the highest test accuracy of approximately 42%, demonstrating its ability to capture complex spatial patterns and features within images. This result indicates that CNNs are a robust choice for image classification tasks, especially when dealing with intricate datasets like CIFAR-100. The consistent increase in accuracy during training and validation suggests effective learning and convergence.

The SVM model, utilizing a Radial Basis Function (RBF) kernel and Principal Component Analysis (PCA), achieved a test accuracy of 24.23%. This performance shows that SVMs, with dimensionality reduction, can effectively classify complex data. The consistent convergence speed and reasonable accuracy make SVMs a suitable alternative in scenarios where deep learning may not be feasible.

The ANN model, however, exhibited a limited test accuracy of 1.94%, suggesting that the simpler architecture might not be sufficient for complex datasets like CIFAR-100. This result indicates potential overfitting or a lack of complexity to capture the diverse features in the dataset. Further tuning or a more complex architecture could be required to improve the ANN's performance.

In summary, CNNs proved to be the most effective in terms of accuracy and convergence speed, while SVM with PCA also demonstrated consistent performance. ANN showed limited accuracy, pointing to the need for additional tuning or complexity. These findings underscore the importance of choosing the right model for image classification tasks, considering factors like dataset complexity and computational efficiency.