MACHINE LEARNING LAB REPORT

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INTRODUCTIONS

This project aims to create a system that can classify vehicle types from images using machine learning. Two methods were explored: a traditional one using Histogram of Oriented Gradients (HOG) features with a Support Vector Machine (SVM), and a more modern approach using a Convolutional Neural Network (CNN). By comparing both methods, the goal is to understand the strengths and weaknesses of each in solving image classification problems.

Dataset Description

The vehicle type recognition dataset contains images of vehicles, sorted by their type. The dataset includes images of various vehicle categories, such as:

- Car
- Bus
- Motorcycle
- Truck

The dataset is ideal for image classification tasks because it contains images taken under different conditions, such as different angles, lighting, and backgrounds. This variety makes the dataset both challenging and interesting for testing machine learning models.

Important features of the dataset include:

- Classes: Includes various vehicle types like cars, buses, motorcycles, and trucks.
- Image Size: All images were resized to 64x64 pixels for consistency.

- Normalization: Pixel values were scaled to a range of [0, 1] for deep learning models.
- Train/Test Split: 80% of the data was used for training, and 20% for testing.

Methodology

In this project, we used both traditional machine learning methods and deep learning (CNN) models to classify vehicle types.

Data preparation to get the data ready for training:

- Image resizing: All images were resized to the same size (e.g., 224x224) to match the input requirements of the models.
- Normalization: The pixel values were scaled to a range of 0-1 to help with the training process.
- Data augmentation: We applied techniques like rotation, zoom, and horizontal flipping to increase the dataset size and make the model more reliable.

Traditional Machine Learning Approach

For traditional methods, we used feature extraction techniques like:

- Histogram of Oriented Gradients (HOG)
- Color histograms
- Local Binary Patterns (LBP)

We then trained machine learning models such as:

- Support Vector Machine (SVM)
- Random Forest
- K-Nearest Neighbors (KNN)

These models were trained using the features we extracted.

Deep learning approach: CNN
We also trained a Convolutional Neural Network (CNN), which learns the features directly from the raw image data. The network included:

- Multiple Conv2D layers with ReLU activation to extract spatial features.
- MaxPooling2D layers to reduce the size of the data.
- A Flatten layer to turn 2D feature maps into a 1D vector.
- Dense layers for classification, with a softmax output layer to predict the class probabilities.

We also used transfer learning with pre-trained models like VGG16 or ResNet, which had already learned basic features like edges and textures from large datasets like ImageNet.

Model Evaluation
The models were evaluated using the following metrics:

- Accuracy
- Confusion Matrix
- Precision and Recall

We divided the dataset into training, validation, and test sets to make sure the models were generalizing well.

Results and Discussion

After training the models, we looked at how well both traditional machine learning models and CNN-based models performed.

Traditional Machine Learning Models

- SVM: The SVM model did okay, but it was limited because it relied on features that were manually chosen and was a simple model.
- Random Forest: This model did a bit better than SVM.
- KNN: The KNN model performed similarly to Random Forest.

These traditional models had trouble with the complex nature of image data because they depended on features that were manually extracted and couldn't capture all the details in the images.

CNN Model

- The CNN model did much better than the traditional models. With a basic CNN, using pre-trained models like VGG16 made it even better for transfer learning and helped the model by using features that had already been learned, improving its ability to recognize different types of vehicles.

The confusion matrix showed that the model had some trouble telling the difference between motorcycles and cars, possibly because they have similar sizes and shapes in some images.

Visualizations when we looked at some of the predictions made by the CNN model to see how it was doing. There were a few misclassifications, especially with vehicles that looked similar (like a bus and a truck in the same pose). However, overall, the model did a good job of classifying the vehicles correctly.

CONCLUSIONS

To sum up, this project showed that Convolutional Neural Networks (CNNs) are highly effective for classifying vehicles based on images. While traditional machine learning methods could handle the task to some degree, CNNs performed much better because they can automatically learn important features from the data. Using transfer learning also boosted the model's accuracy, making it a strong approach for identifying different vehicle types.

For future improvements, we could look into using more advanced CNN models like ResNet or EfficientNet, and try out more data augmentation techniques to make the model even more reliable. Additionally, expanding the dataset with a wider variety of vehicle images could help the model perform better on new, unseen data.