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MACHINE LEARNING LAB REPORT

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INTRODUCTIONS

The goal of this project is to use machine learning to develop a system that can identify different kinds of vehicles from photos. A conventional approach utilising Histogram of Orientated Gradients (HOG) features with a Convolutional Neural Networks (CNNs), a more recent technique, and Support Vector Machines (SVM). Understanding the advantages and disadvantages of each approach in resolving picture classification issues is the aim of this comparison.

Dataset Description

Images of automobiles are arranged according to their type in the vehicle type recognition dataset. Images of different vehicle classifications are included in the dataset, including:

- Car
- Bus
- Motorcycle
- truck

Because the dataset includes photos shot in a variety of settings, including various lighting conditions, backdrops, and angles, it is perfect for picture classification tasks. The dataset is intriguing and hard for testing machine learning models because of its diversity.
Among the dataset's salient characteristics are:

- Classes: Contains a range of vehicle kinds, including trucks, cars, buses, and motorbikes.
- For consistency, all pictures were resized to 64 by 64 pixels.
- Normalisation: For deep learning models, pixel values were scaled to a range of [0, 1].
- 20% of the data was used for testing, while the remaining 80% was used for training.

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.

Additionally, we trained a Convolutional Neural Network (CNN), which
uses the raw picture data to directly learn the features. Several Conv2D layers with ReLU activation were part of the network to extract spatial characteristics.

- To minimise the size of the data, use MaxPooling2D layers.
- To convert 2D feature maps into 1D vectors, use a flatten layer.
- Using a softmax output layer to forecast the class probabilities, dense layers are used for classification.

With pre-trained models like VGG16 or ResNet, which had previously picked up fundamental characteristics like edges and textures from sizable datasets like ImageNet, we also employed transfer learning.

Assessment of the Model

The following measures were used to assess the models:

- Accuracy
- The Confusion Matrix
- Accuracy and Memory

To ensure that the models were accurate, we separated the dataset into training, validation, and test sets.

Results and Discussion

Following model training, we examined the performance of CNN-based and conventional machine learning models Conventional Models for Machine Learning

SVM: The SVM model performed reasonably well, but it had limitations because it was a simple model that depended on manually selected characteristics.

Random Forest: Compared to SVM, this model performed somewhat better.
KNN: Random Forest and the KNN model both had comparable results.
Because they relied on manually extracted characteristics and were unable to capture all the nuances in the photos, these traditional models struggled with the complex nature of image data.

CNN Model:

CNN Model Compared to the traditional models, the CNN model performed significantly better. Using pre-trained models like VGG16 with a simple CNN made it even more effective for transfer learning and aided the model in identifying various vehicle kinds by utilising previously learnt attributes.The model struggled to distinguish between motorcycles and vehicles, according to the confusion matrix, perhaps as a result of their comparable sizes and shapes in some photos. visualisations when we examined a few of the CNN model's predictions to gauge its performance. A few vehicles were misclassified, particularly when they had similar appearances (such as a truck and a bus in the same stance). But all in all, the model performed well

CONCLUSIONS

In conclusion, this study demonstrated the great efficacy of Convolutional Neural Networks (CNNs) in the classification of automobiles from pictures.
Although the assignment might be partially completed by conventional machine learning techniques,

Due to their ability to automatically extract significant features from the data, CNNs fared substantially better. The model's accuracy was also increased by using transfer learning, giving it a powerful method for differentiating between vehicle types.

In the future, we might investigate the use of more sophisticated CNN models, such as ResNet or EfficientNet, and experiment with additional data augmentation strategies to further strengthen the model's dependability. Furthermore, adding more vehicle photos to the dataset can improve the model's performance on fresh, untested data.