Image Features Report:

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In order to show how neural networks can be used to achieve competitive accuracy in image classification tasks, this study describes the creation and assessment of a two-layer neural network classifier. The classifier is meant to classify images based on extracted features.

Accomplishments Description

The efforts and results of successfully classifying photos using a two-layer neural network trained on extracted features are compiled in this article. In order to investigate if neural networks are more effective than conventional linear classifiers, the project produced a noteworthy classification accuracy of 56.5% on the test set. The ultimate model demonstrated the neural network's potential in picture categorization tasks by surpassing the original target of over 55% accuracy.

Training Process: Initial Parameters: Learning rates, regularization strengths, and decay rates were the main emphasis of the initial set of hyperparameter combinations used in the training process.
Epochs Trained: The model underwent 14 epochs of training, during which time iterations of both training and validation accuracy showed appreciable gains.

Key tasks:

- **Feature extraction**: Produced a feature set that enhanced model performance by extracting features from the training dataset using color histograms and the Histogram of Oriented Gradients (HOG).
- **Model Training:** Using a range of hyperparameter combinations, a two-layer neural network was trained on the features of the retrieved image. During cross-validation, the best model obtained a validation accuracy of 60%.
- **Model Evaluation:** The best neural network on the test set was evaluated, and it was able to achieve a classification accuracy of 56.5%, exceeding the project's 55% aim.
- **Model Development:** To handle picture information and enable better feature representation and learning than raw pixel input, a two-layer neural network model (TwoLayerNet) was developed.

Missed Points:

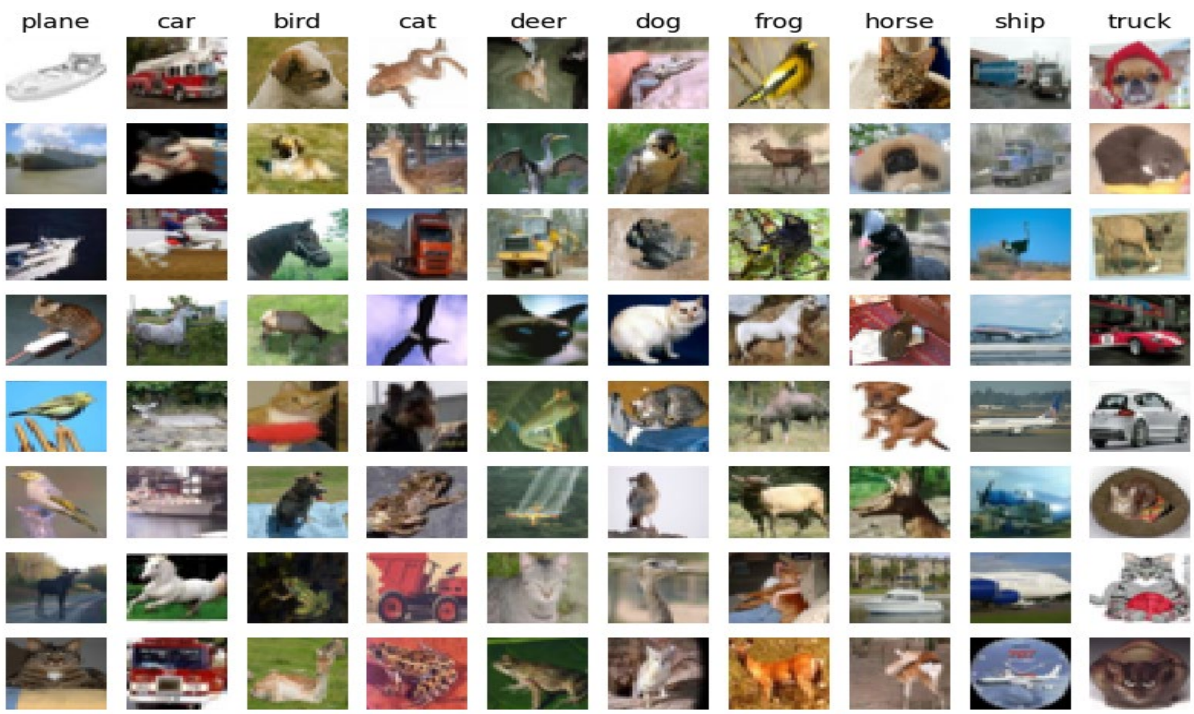
- **Feature Exploration:** Although color histogram and HOG features worked well, alternative features that could have improved accuracy further were not investigated, such as texture descriptors or deep features from pre-trained models (e.g., VGG16, ResNet).
- **Model Complexity:** The two-layer architecture worked well, but since deeper networks (such convolutional neural networks) can learn hierarchical feature representations, they might do even better.
  Performance Analysis: Not all of the incorrectly classified images were thoroughly examined. Gaining insight into the causes of misclassifications may enable more focused feature engineering or data gathering initiatives.

Explanation of Implementation Decisions

- In order to balance model complexity and computing efficiency, a two-layer neural network was chosen. This allows for successful learning while preventing overfitting on the training set.
- Previous experiments that demonstrated better performance when compared to raw pixel inputs served as the catalyst for the introduction of HOG features. The decision was supported by preliminary testing that showed improved accuracy after training.
- The process of hyperparameter tuning was methodical, evaluating various setups to guarantee peak efficiency and extrapolation to the validation set.

Critical Thinking and Analysis

- The process of hyperparameter tuning made clear how sensitive neural network performance is to regularization strengths and learning rates, emphasizing how crucial it is to adjust these parameters precisely to prevent overfitting and guarantee sufficient learning.
- The model benefited from both learning rate decay and adequate regularization, as revealed by the trends in validation accuracy, as demonstrated by the increase in validation accuracy across subsequent epochs.
- Hyperparameter Tuning: Methodically investigated hyperparameter setups, such as: Rate of Learning: 0.1 to 0.105. Normalization: 2e–5 to 3e–5. Rate of Decay: 0.9 to 1.0
- Training and Evaluation: Values of Losses Seen: Loss at Start: 2.302614 Complete Loss: 0.973093. Training Accuracy Development: Train Accrual: 0.087; Val Accrual: 0.107, Epoch 0. Train Accrual: 0.694; Val Accrual: 0.598 in Epoch 14



The Reason Behind These Outcomes:

1. The two-layer neural network's 56.5% accuracy rate validates the use of neural networks in this challenge by showing that it can learn and generalize from the given visual information.
2. The requirement for extensive exploration in model training is further shown by the model's performance increases during training, which indicate that the chosen hyperparameters were appropriate for the dataset.

Next Actions:

1. **Data Augmentation:** To increase the training dataset artificially and boost the accuracy and resilience of the model, apply rotation, scaling, and flipping procedures.
2. **Explore Advanced Architectures:** Examine more complex neural network topologies, such as convolutional neural networks (CNNs), which can take advantage of spatial hierarchies in features and are more appropriate for handling picture data.
3. **Evaluation of Performance:** Examine misclassified samples in detail to find trends that might guide feature engineering or training dataset modifications.
4. **Experiment With Various Feature Sets:** Examine different feature extraction methods to see how they affect classification accuracy, such as features derived from pre-trained networks that are based on deep learning.

Supporting References

Visualizing Machine Learning Models, CNN, Hyperparameter Tuning, ML Train/Test