Image Classification: US License Plates

Executive Summary

The objective of the project was to develop an effective machine learning model for classifying US license plate images into one of the 50 states. The dataset, consisting of original images from all states, posed a challenging task. The approach involved exploring both non-neural network and neural network classifiers. While non-neural network models demonstrated limited success, neural networks, especially the Convolutional Neural Network (CNN) and Transfer Learning models, showcased promising accuracy levels.

Dataset Overview

The dataset comprises high-quality images of US license plates, with each of the 50 states represented as a distinct class. Images are standardized at 128 pixels X 224 pixels X 3 channels in jpg format. Notably, all images are originals with no augmentation, and license plates occupy at least 90% of the pixels. The accompanying CSV file facilitates the creation of training, validation, and test sets.

Data Wrangling

Primarily, two actions were taken during the data wrangling process.

1. **Balance Analysis:**
    - The dataset was analyzed for balance or imbalance. It was found that the given dataset was relatively balanced, with around 147 license plate images per state. Additionally, the maximum and minimum number of images for a given state were 175 and 121, respectively. The information provided in the CSV file for the data matched the folder contents as well.
2. **Visualization of License Plate Images:**
    - To gain insights into the dataset, four license plate images were visualized for each state by accessing the images in each state folder. This visual exploration provided a qualitative understanding of the diversity and characteristics of license plate images for different states.

Part 1. Non-Neural Network Classifiers

Model A: Random Forest Classifier

- **Conceptual Details:**
    - The Random Forest Classifier is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes as the prediction. Each decision tree is built on a random subset of features and contributes to the final decision.
- **Accuracy Results:**
    - Provided only a 4% accuracy on the test data, falling short of the project's success criteria.

Model B: KNN Classifier

- **Conceptual Details:**
    - K-Nearest Neighbors (KNN) is a non-parametric and lazy learning algorithm that classifies an object based on its k-nearest neighbors in the feature space. KNN determines the class of a data point by a majority vote of its k-nearest neighbors.
- **Accuracy Results:**
    - Achieved a slightly higher accuracy of 17% on the test data, yet it remained below the desired threshold.

Part 2. Neural Network Classifiers

Model A: Multilevel Perceptron (MLP) Classifier

- **Conceptual Details:**
    - The Multilevel Perceptron (MLP) is a feedforward artificial neural network consisting of an input layer, hidden layers, and an output layer. Each neuron in a layer is connected to every neuron in the subsequent layer. MLP learns through backpropagation, adjusting weights to minimize the error.
- **Accuracy Results:**
    - Despite iterations with hidden layers and increased epochs, the MLP Classifier plateaued at 30% accuracy on the test data. Further exploration of

hyperparameters, such as the number of hidden layers and epochs, did not result in significant accuracy improvement. The limitations of MLP for this specific image classification task might be attributed to the complexity and intricacies of capturing state-specific features in license plates.

Model B: Convolutional Neural Network (CNN) Classifier

- **Conceptual Details:**
    - Convolutional Neural Networks (CNNs) are specialized neural networks designed for image recognition. They leverage convolutional layers to automatically learn spatial hierarchies of features. Max pooling is applied to reduce the spatial dimensions of the output volume, and batch normalization stabilizes and accelerates the training process.
- **Accuracy Results:**
    - Emerged as a stronger contender, achieving 67% accuracy on the test data by incorporating 32 filters, max pooling 2D, and batch normalization for different layers. CNNs excel at image-related tasks due to their ability to automatically learn hierarchical representations of features. The convolutional layers capture local patterns, and the pooling layers reduce spatial dimensions, making the model effective in discerning complex patterns within license plate images.

Model C: Transfer Learning Implementation

- **Conceptual Details:**
    - Transfer Learning involves utilizing pre-trained models for a new, similar task. In this project, the ResNet architecture, a deep learning model, was fine-tuned for license plate classification. Fine-tuning adjusts the pre-trained model's parameters to adapt it to the specific dataset.
- **Accuracy Results:**
    - Demonstrated remarkable progress, initially achieving 76% accuracy on the test data, and further excelling to 83% with data augmentation. Transfer Learning leverages the knowledge gained from training on a large dataset (in this case, the pre-trained ResNet model) and applies it to a new, smaller dataset. The pre-trained ResNet model already possesses a rich set of features useful for image recognition, allowing for more efficient and effective learning on the license plate dataset.

Recommendations and Future Research

Recommendations

1. **Optimize CNN Parameters:**
    - Further tuning the parameters of the CNN model, such as the number of filters, kernel sizes, and the depth of the network, could potentially enhance accuracy.
2. **Explore Ensemble Methods:**
    - Combining the strengths of different models through ensemble methods, such as stacking or bagging, may lead to improved overall performance.
3. **Continued Data Augmentation:**
    - Expanding the dataset through additional data augmentation techniques could contribute to enhancing the robustness and generalization of the models.

Future Research

1. **Anomaly Detection:**
    - Investigating anomaly detection techniques for identifying and handling outlier license plates or novel classes that are not present in the training data.
2. **Explainability and Interpretability:**
    - Incorporating methods to make the models more interpretable, especially in scenarios where transparency is crucial, such as law enforcement applications.
3. **Real-time Implementation:**
    - Exploring the feasibility of deploying the model for real-time license plate classification applications, considering speed and efficiency requirements.

In conclusion, while non-neural network models struggled to meet the project's criteria, neural network models, especially CNN and Transfer Learning, exhibited promising results. Further refinement and exploration of recommendations could lead to a more accurate and robust license plate classification system.