A Machine Learning Model for Autonomous Driving

This presentation delves into the development of a machine learning model for autonomous driving. Our goal was to create a system capable of accurately identifying objects in complex traffic scenarios, contributing to the advancement of safe and efficient self-driving vehicles.

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Introduction

1 Project Overview

This project focuses on developing a machine learning model for traffic image classification, a crucial component for autonomous driving systems.

2 Objective

Our objective was to build a model capable of accurately identifying and classifying objects within complex traffic environments, enabling autonomous vehicles to make informed decisions in real-time.

3 Challenge

The primary challenge lies in the complexity of traffic scenes. Objects can be partially occluded, varying in size and orientation, and often appear in cluttered backgrounds. Our model needed to be robust enough to handle these intricate situations.

Methodology: Dataset and Preprocessing

Dataset

We used the Udacity annotated driving dataset, a rich collection of images captured from a vehicle driving in various traffic scenarios. Each image is annotated with bounding boxes and labels, indicating the presence and type of objects within the scene.

Preprocessing

To prepare the data for training, we performed several preprocessing steps. Images were resized to 64×64 pixels for computational efficiency. Additionally, images were converted to grayscale to reduce dimensionality and focus on shape and edge information.

Methodology: Feature Extraction and Models

Feature Extraction

For effective object recognition, we employed the Histogram of Oriented Gradients (HOG) feature descriptor. HOG captures information about edges and shapes within an image, providing a robust representation for object detection.

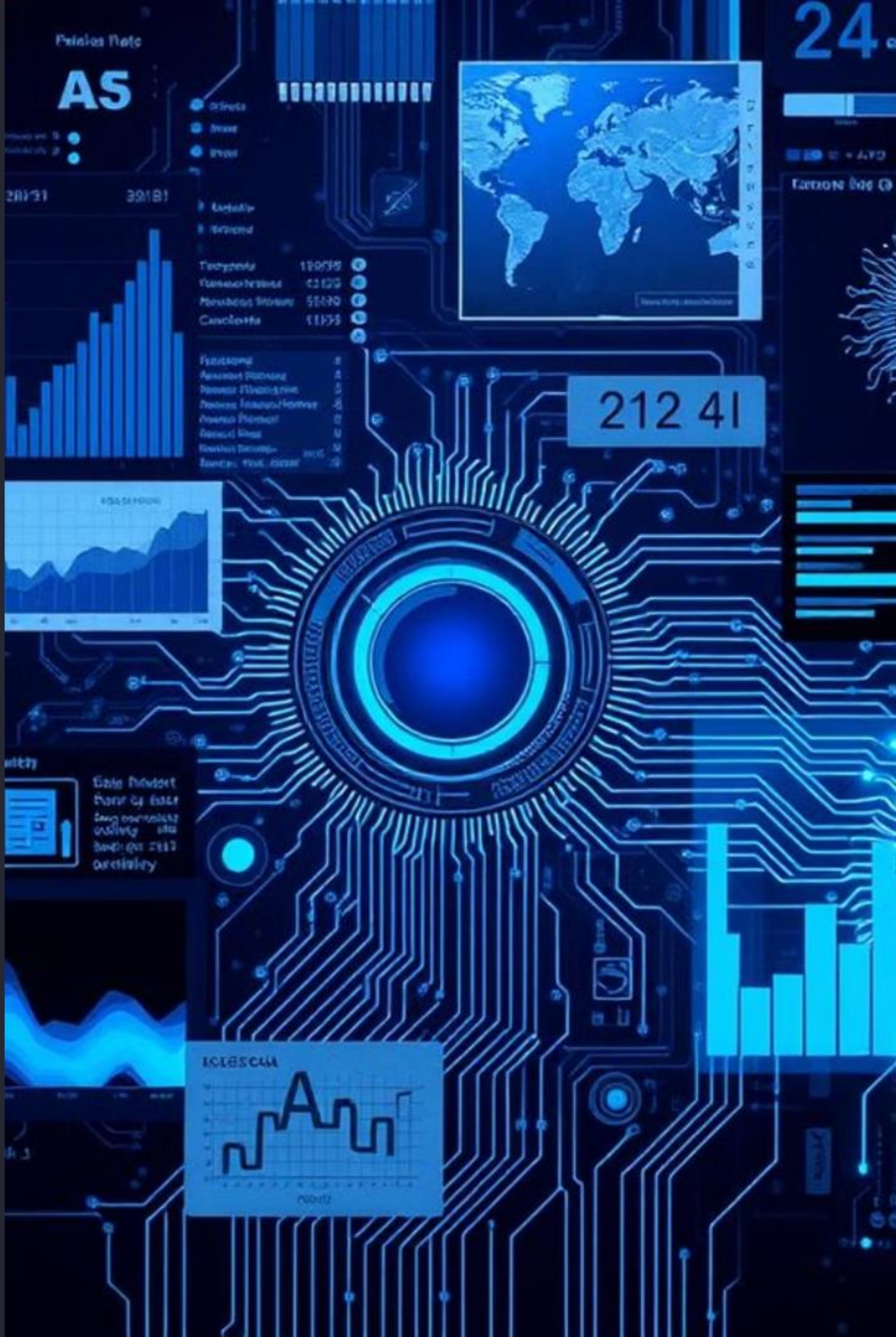
To reduce the dimensionality of the HOG features, we applied Principal Component Analysis (PCA), reducing the feature space to 50 components, while preserving the most significant information.

Models Trained

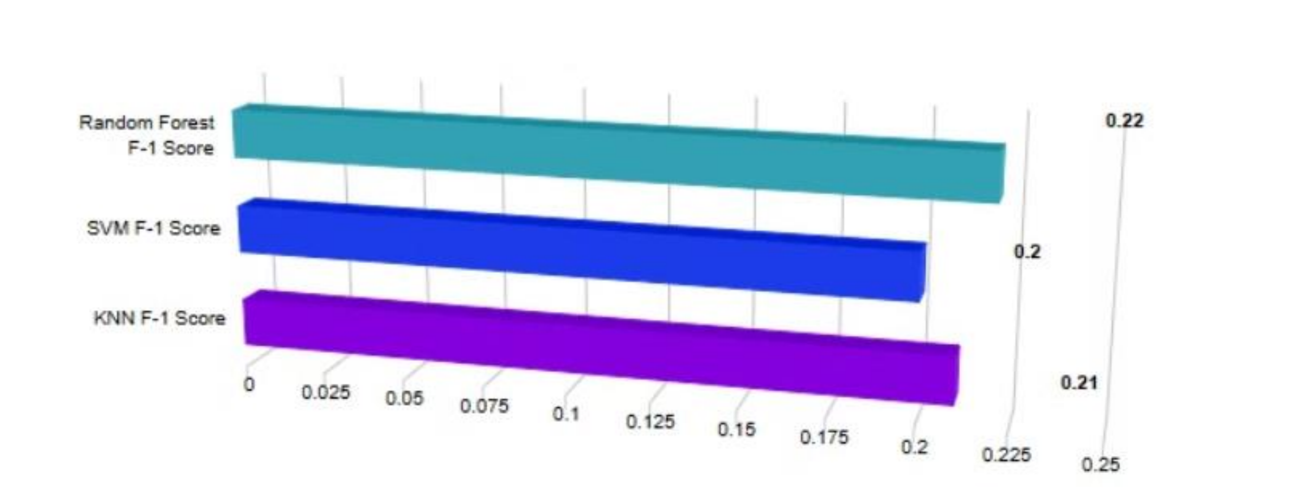
1. Random Forest
2. Support Vector Machine (SVM)
3. K-Nearest Neighbors (KNN)

Results and Evaluation

Model	F1-score	Accuracy
Random Forest	0.22	23%
SVM	0.20	22%
KNN	0.21	22%



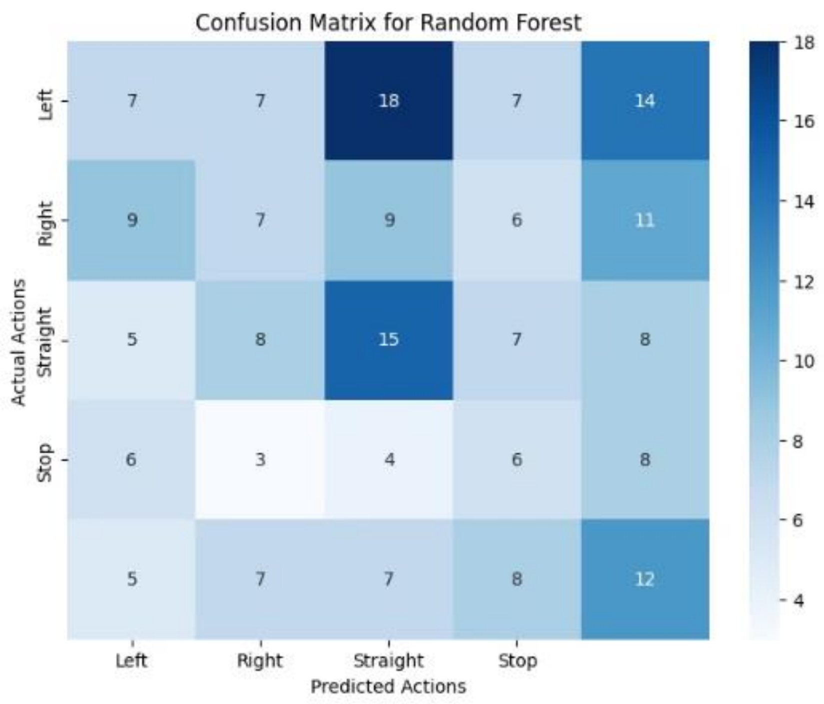
Results and Evaluation



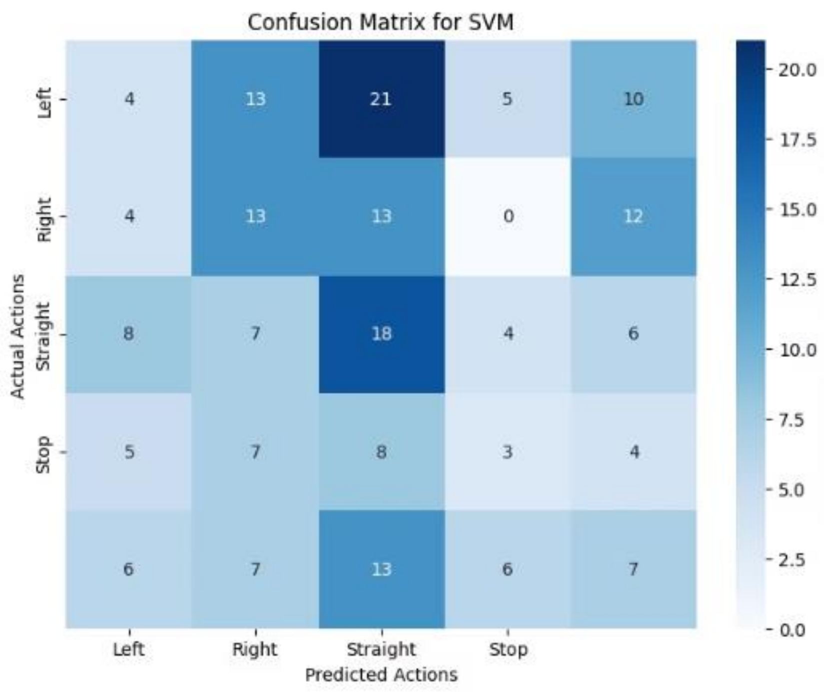
F-1 Score

Accuracy

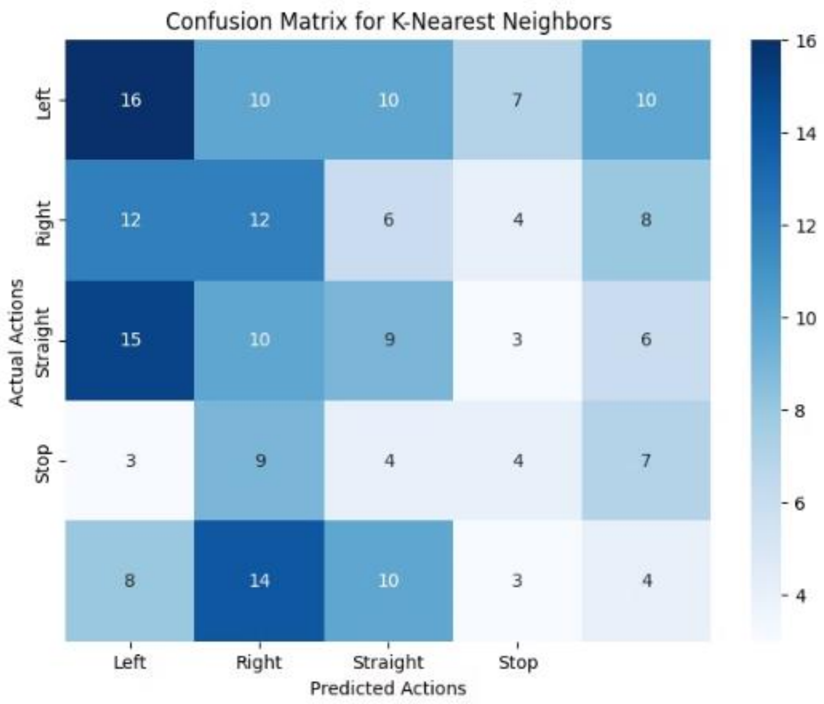
Results and Evaluation



Random Forest



Support Vector Machine (SVM)



K-Nearest Neighbour (KNN)

Conclusion

1 Achievements

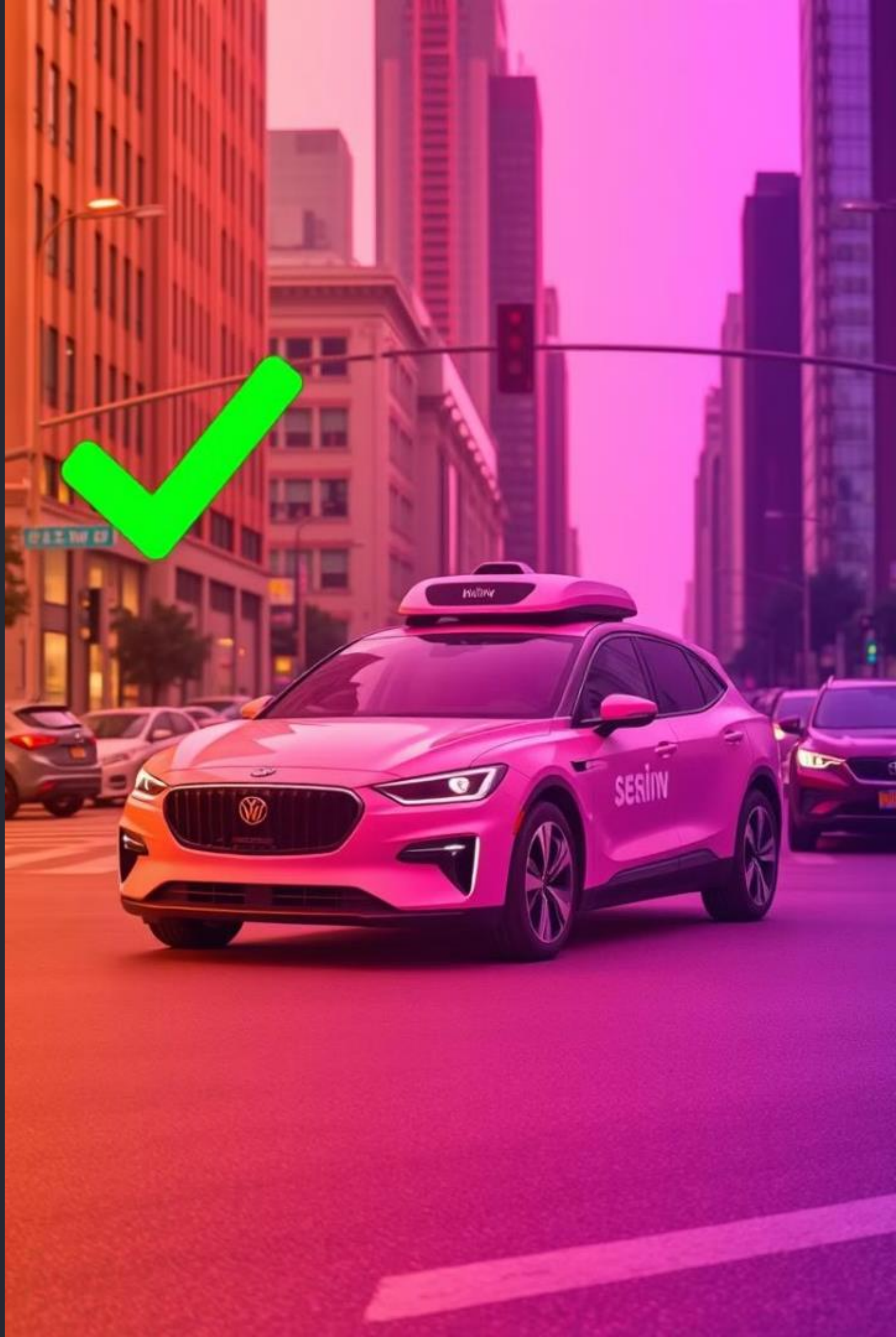
This project successfully developed a machine learning pipeline for traffic image classification, combining HOG feature extraction, PCA dimensionality reduction, and machine learning models.

2 Insights

The Random Forest model demonstrated the best performance among the evaluated models, showcasing its ability to handle the complexity of traffic scenes with reasonable accuracy.

3 Future Work

Future research will focus on exploring deep learning techniques for further accuracy improvements. We aim to investigate convolutional neural networks (CNNs), which have proven successful in complex image recognition tasks. Additionally, we will address the challenge of rare category detection, ensuring that our model can effectively identify objects that occur less frequently in the dataset.



References

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2. Breiman, L. (2001). Random Forests. https://www.stat.berkeley.edu/~breiman/RandomForests/cc_home.htm
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Thank you!