Vehicle Image Classification

DS 4002

Group 15: Alex DeStephanis (leader), Nathan Wan, & Jillian Haig

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Project Details

Motivation: Understand if a machine learning model can be used for vehicle classification into five types: SUV, pickup, sedan, hatchback, or other, to aid law enforcement camera monitoring systems

Research Question: Can a computer vision model successfully classify a vehicle type to an extent that the model can be applied for the betterment of society (i.e. for police camera identification)?

Hypothesis: When comparing the model's predictions to the actual vehicle present in the image data via insights from after completing the softmax output layer, the model will be strong enough to correctly identify vehicle type

Modeling Approach: CNN model, with TensorFlow/Keras (ResNet50) packages. After compiling, layer manipulation, and fine tuning, concluded with K-fold cross validation, accuracy, F1 score, and ROC visualization

Goal: Build an accurate (85% or higher for each class) model that can be used for police to identify vehicles that commit crimes

Data Acquisition & Explanation

Dataset Explanation

- This dataset was retrieved from Mendeley Data [2].
- Python was used to merge the individual images in each folder into one dataset which states the vehicle type along with the image.

Variable Name	Description	Potential Responses
image_path	Image variable using a file path which directs to the image location in Google Colab in the content folder, this is used to open the image in a method which saves computing power.	/content/vehicleimages/hatchback/PHOTO_89.jpg, /content/vehicleimages/sedan/PHOTO_965.jpg
label	String variable which classifies what type of vehicle the image is referring to.	hatchback, other, pickup, suv, sedan

Example Images:

Hatchback:

Other:

Pickup:

Sedan:

SUV:

Analysis Plan & Justification

1. Data Collection & Preprocessing

Vehicle data gathered from an online source, Mendeley Data [2]

2. EDA & Visualization

Discovered that pickups had the highest label count, followed by sedans

3. Modeling Approach

CNN Model with TensorFlow/Keras package, ResNet50, Training, Fine Tuning, K-fold cross validation, Statistics and visualization

Tricky Analysis Decision

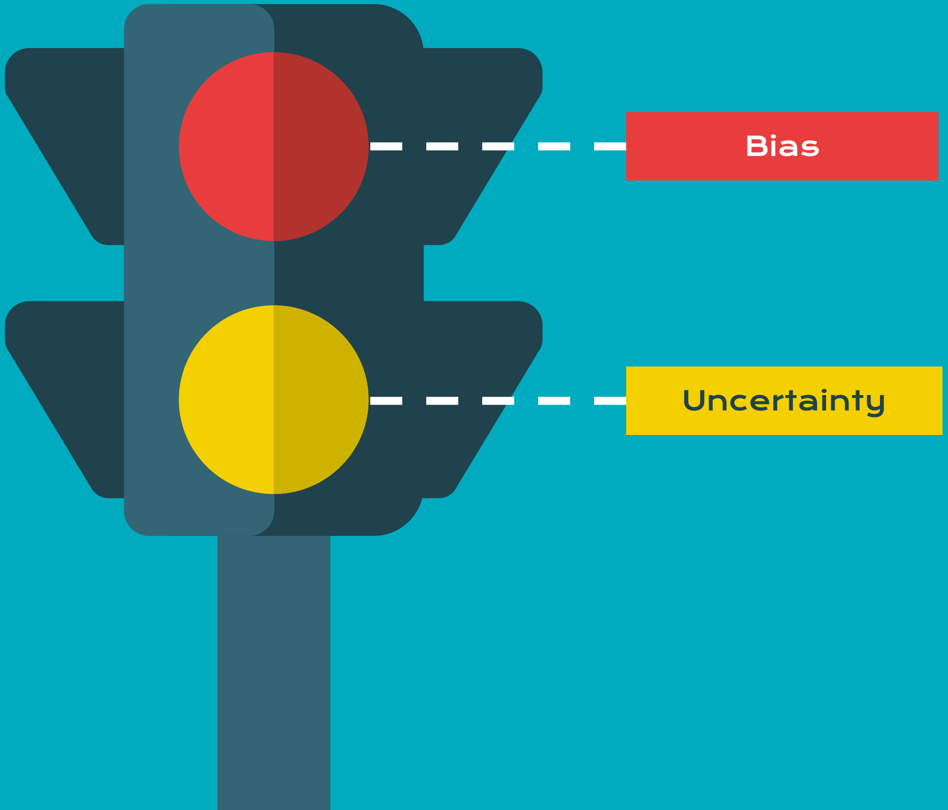
```
val_accuracy: 0.7683

val_accuracy: 0.7592

val_accuracy: 0.7248
```

- Worried about model overfitting due to excessive training
  - Learned about earlystopping within the tensorflow.keras package
  - Stops running each fold early when the val_accuracy fails to reach its previous high two epochs in a row
  - Successfully prevented overfitting

- Increased the number of epochs per fold from 5 to 50
  - This rose the overall accuracy and with early stopping provided no downside

- Unfroze top layers of ResNet50 for fine-tuning
  - Goal was to allow for more complex patterns of vehicles to be recognized

Bias & Uncertainty Validation



- The group only used one dataset of vehicle images, whereas testing more data with different photos could have helped the group understand the results better.
- Dataset was made for image analysis, is it applicable to real world images?
- Poor image quality

- Vehicle images may come from a different country, would be better to focus on one country if possible
- Model and year of vehicle

Results & Conclusion

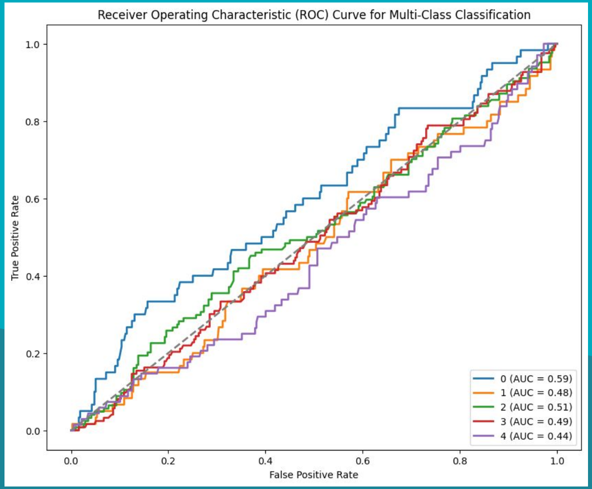
Model failed to reach our accuracy and F1 score goals by a large margin, which rejects our hypothesis

- It performed much better for sedan and pickup than the other types
- Better to just compare pickup and sedan, extra vehicle types were too difficult for the model to discern

Concerns:

- Sizing could play an effect as ResNet50 requires 224x224
- Hatchback and SUV look too similar for them to be separated with this model

```
Average accuracy for each label:
pickup: 0.4040
suv: 0.1176
other: 0.1283
hatchback: 0.0927
sedan: 0.2951

Average overall accuracy: 0.2473
Average weighted F1 score: 0.2333
```



Next Steps

New Lines of Exploration

- Company logo recognition
- License plate classification

New Questions

- How do vehicle design differences play a role in the model's performance?
- Would the model improve in terms of accuracy and F1 score if only looking at sedan and pickup vehicle types?

Improvements

- Hone in on sedan and pickup
- Rework model layer freezing and fine tuning
- Produce better quality images that match the size specifications for ResNet50 (224x224)

References

[1] A. Snider, “Traffic Safety Cameras: New Guide Explores Benefits, Challenges of Effective Automated Enforcement | GHSA,” www.ghsa.org, Dec. 05, 2023. https://www.ghsa.org/resources/news-releases/automated-enforcement-report23 (accessed Nov. 06, 2024).

[2] Narong Boonsirisumpun, “Vehicle Type Image Dataset (Version 2): VTID2,” Mendeley Data, vol. 2, no. 10.17632/htsngg9tpc.2, Nov. 2021, Accessed: Nov. 06, 2024. [Online]. Available: https://data.mendeley.com/datasets/htsngg9tpc/2

GitHub: https://github.com/jillianhaig/Project3_DS4002/tree/main

Questions?

Thanks!