



PARKING SPACE DETECTION **COMPUTER VISION PROJECT**

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PROJECT GOAL

The goal of the project is to build a model using computer vision to detect and predict empty or occupied parking spaces, with a focus on intelligent parking management.



CHALLENGES & SOLUTIONS

Challenge: The business goal was clear as a classification problem, but the challenge was in determining the most effective computer vision workflow.



Solution: Transfer learning was chosen as the optimal approach, using pre-trained models like MobileNet to enable faster development.

CHALLENGES & SOLUTIONS

Challenges:

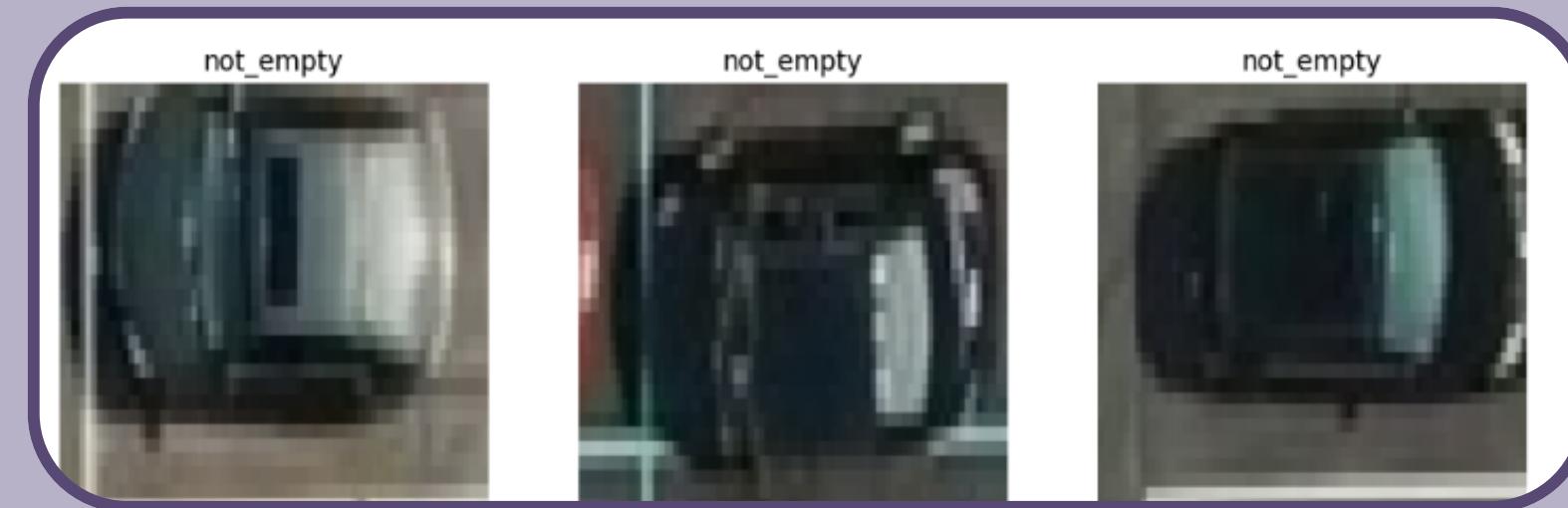
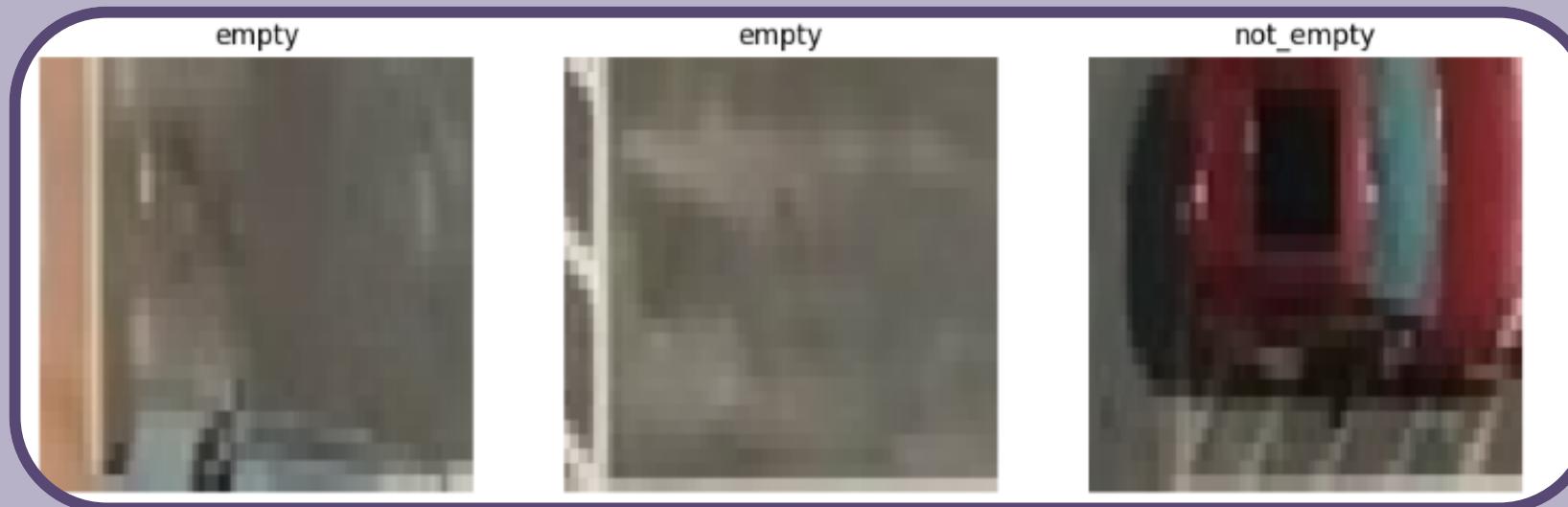
- Execution time: The process took a significant amount of time, slowing down progress due to the large data size.
- Google Colab limitations: The environment struggled with video and multi-frame loading, affecting performance.



Solution: Overcame challenges by limiting the number of frames after the video was loaded, improving efficiency.

DATASET OVERVIEW

- The dataset contains 6090 images , labeled as empty or not empty and 1 video of a parking lot.
- The images are organized to indicate the occupancy status, while the video captures real-time changes in occupancy.
- Additionally, some images feature cropped regions (mask) to focus on parking spaces.



METHODOLOGY

ETL

- Created a functions that loads the dataset stored on Google Drive within the Colab environment.
- The Data is retrieved from 2 folders labeled as empty (representing the empty spots on a parking lot) and not empty (representing the not empty spots).



METHODOLOGY

DATA MODELING

- A function is created to automatically extract class names from the folder names.
- Used the class (`ImageDataGenerator` from tensorflow) to automatically split the dataset into training and validation sets.



- The batch size and target size control how many images are processed at once and ensure they are resized correctly.
- Additionally, the pixel values are scaled to a range of 0 to 1, ensuring the data is consistent for the model.

METHODOLOGY

MODEL SELECTION

CNN

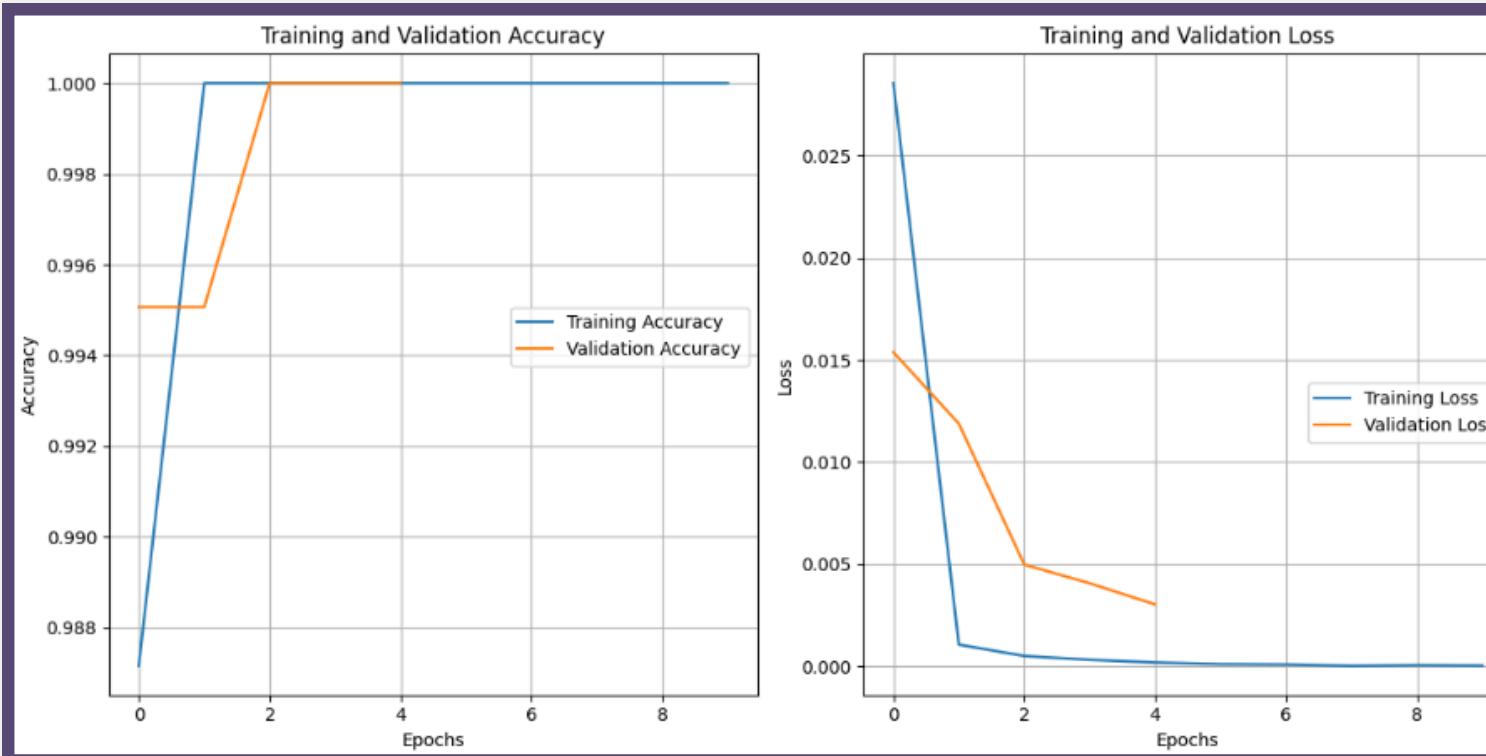
- Designed a CNN with sequential layers, including convolution, max-pooling, and fully connected layers for binary classification.
- Compiled the model using the Adam optimizer, binary cross-entropy loss, and accuracy metric.
- Trained the model for 10 epochs with a data generator, ensuring efficient batch processing.



METHODOLOGY

MODEL SELECTION

Mobile Net

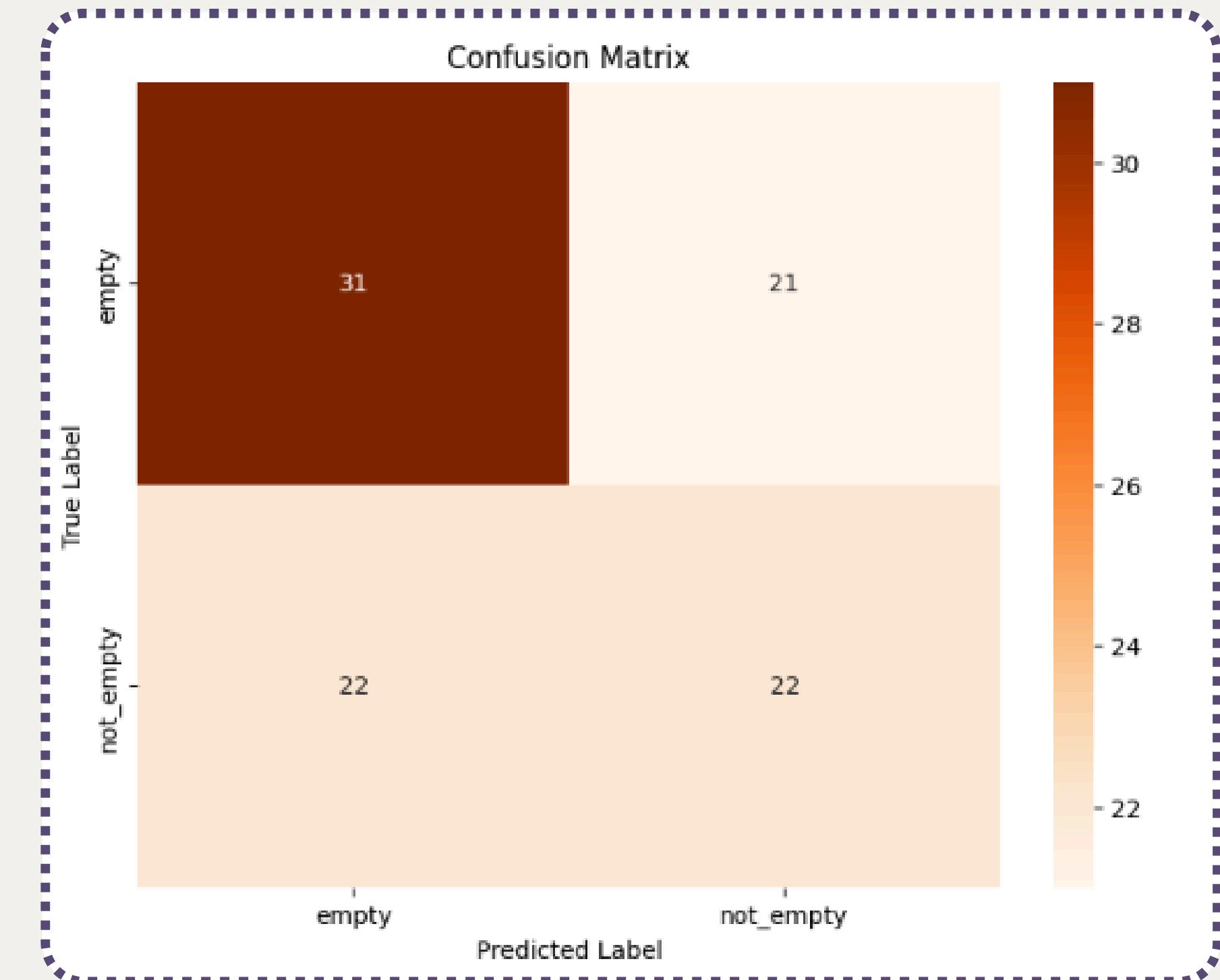


- Load the pre-trained MobileNet model (without the top layers, transfer learning model) and freeze its weights for feature extraction.
- Add global average pooling, a dense layer with ReLU activation, and a final dense layer with a sigmoid activation for binary classification.
- Compile the model using the Adam optimizer and binary cross-entropy loss, then train it on the data for 10 epochs.

MOBILE NET EVALUATION

CONFUSION MATRIX

- The model captures a balanced distribution between both classes, with true positives exceeding the other cases in the confusion matrix by 10.
- The primary focus should be on reducing false negatives while simultaneously improving accuracy, precision, and recall scores



MOBILE NET EVALUATION

METRICS

Classification Report:

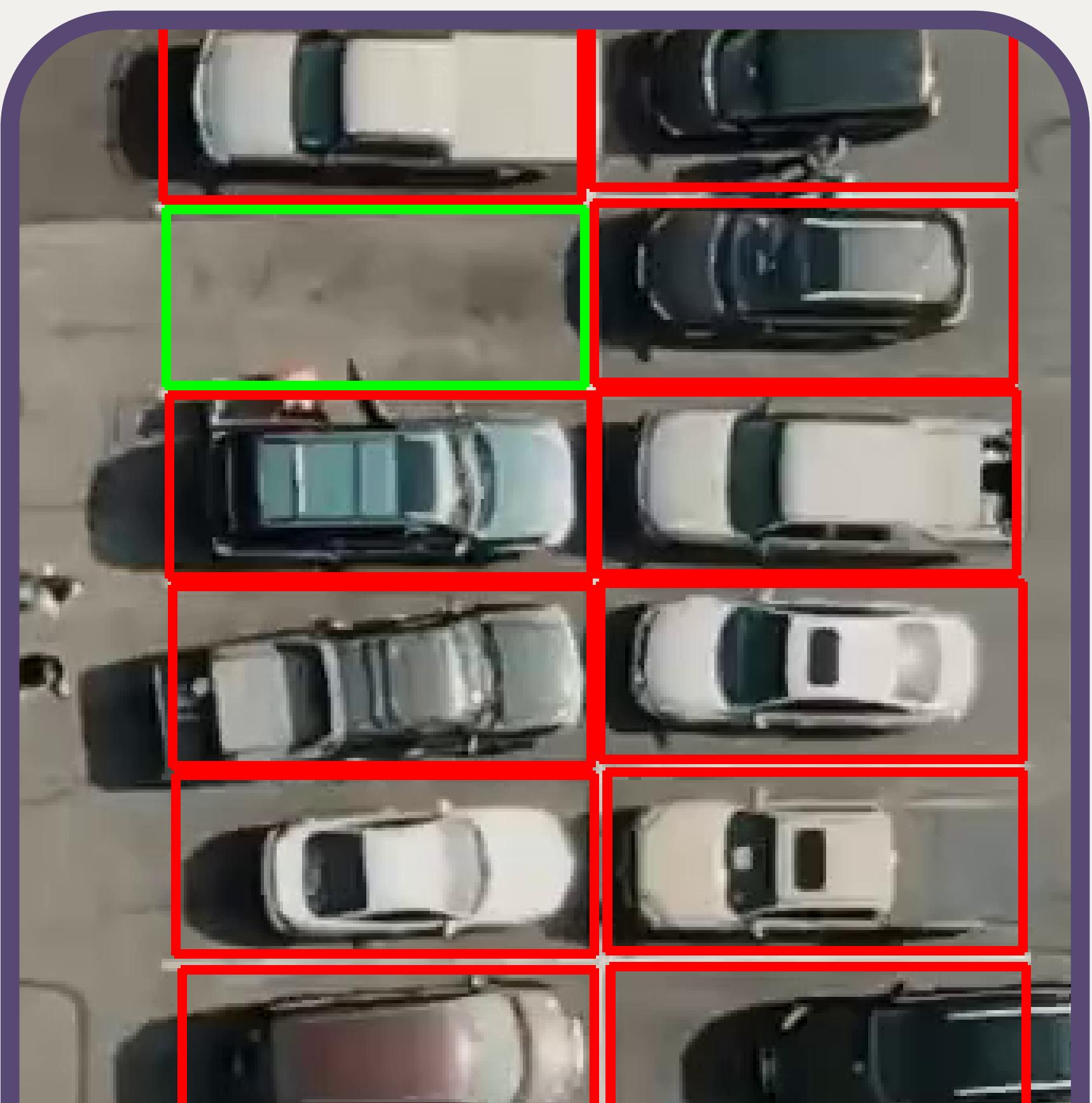
	precision	recall	f1-score	support
empty	0.58	0.60	0.59	52
not_empty	0.51	0.50	0.51	44
accuracy			0.55	96
macro avg	0.55	0.55	0.55	96
weighted avg	0.55	0.55	0.55	96

- The model struggles to differentiate between the two classes effectively with scores close to 0.5.
- The empty class is predicted slightly better than the not empty class, with an F1-score of 0.59 vs. 0.51.
- Improvement needed: Perform data augmentation to evaluate its impact on model performance and apply fine-tuning to assess whether it leads to improved results.

MOBILE NET EVALUATION

- Used MobileNet model, enhanced with two functions to visually distinguish parking spots: empty spots are highlighted in green, and occupied spots are marked in red.
- Improvements needed: Expanded the model's evaluation by testing it on a larger dataset of parking spots to assess its performance at a larger scale.

PREDICTED OUTCOMES VIDEOS



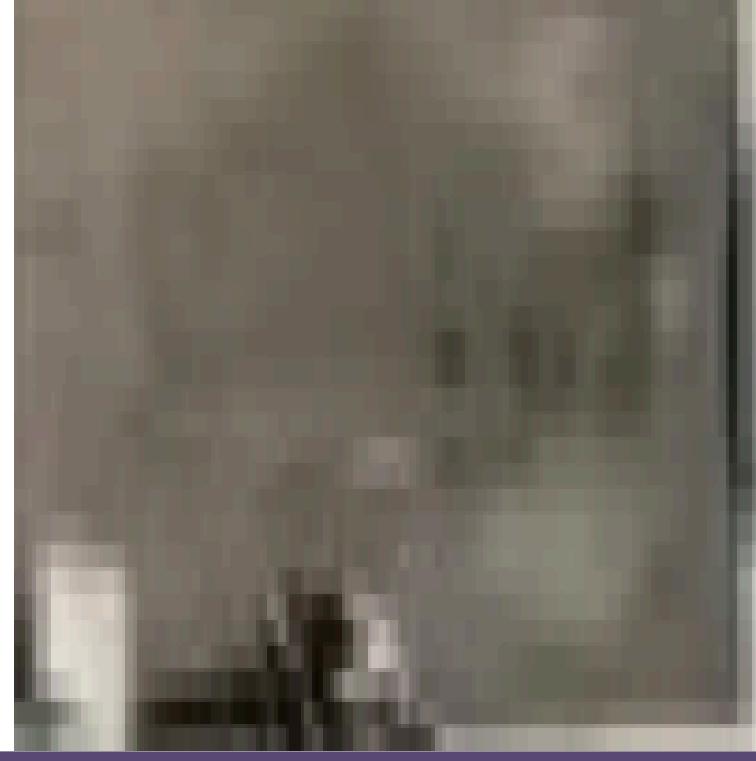
MOBILE NET EVALUATION

PREDICTED OUTCOMES IMAGES

True: not_empty
Pred: not_empty



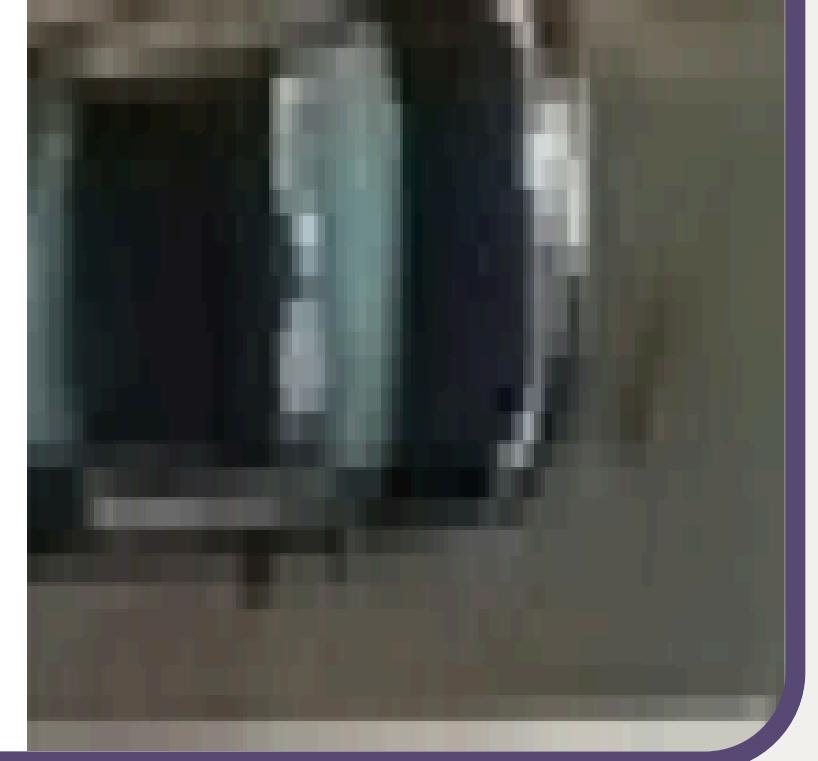
True: empty
Pred: empty



True: not_empty
Pred: not_empty



True: not_empty
Pred: not_empty



NEXT STEPS

- Explore alternative transfer learning models to improve classification performance.
- Implement fine-tuning to optimize model weights for the specific parking spot detection task.
- Apply data augmentation techniques to improve model generalization.
- Use additional evaluation metrics, such as the ROC curve, to gain deeper insights into the model's performance.
- Focus on enhancing key metrics in the classification report, including precision, recall, and accuracy.



THANK YOU!

