Can Deniz SALMAN
Umut Can ORAL

COMPREHENSIVE CAR DAMAGE DETECTION

Introduction

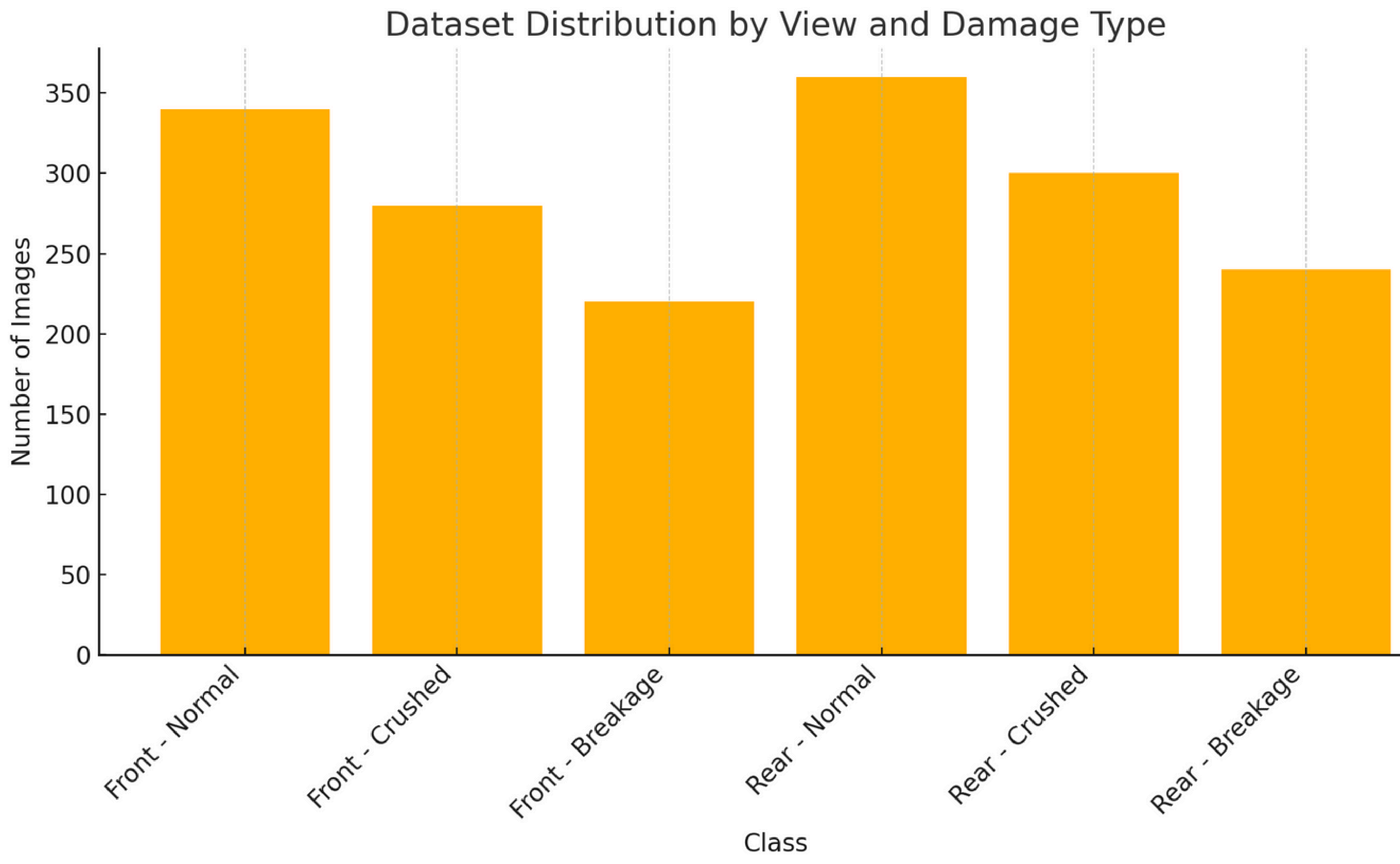
The analysis of traffic accidents and vehicle damage is a time-consuming and costly process for insurance companies and car repair shops. This project aims to detect damage from vehicle images using deep learning-based imclassification techniques. The system determines whether the front or the rear of a vehicle is visible (view classification) and then automatically detects whether there is damage in this area and if there is damage, its type (normal, crushed, broken).

Dataset Overview

The dataset used in this project consists of vehicle images captured from different angles (front/rear) and labeled with their corresponding damage conditions.

It is organized into 6 folders representing each class:

- front_crushed
- front_breakage
- front_normal
- rear_crushed
- rear_breakage
- rear_normal



Preparing the Dataset for Multitask Learning

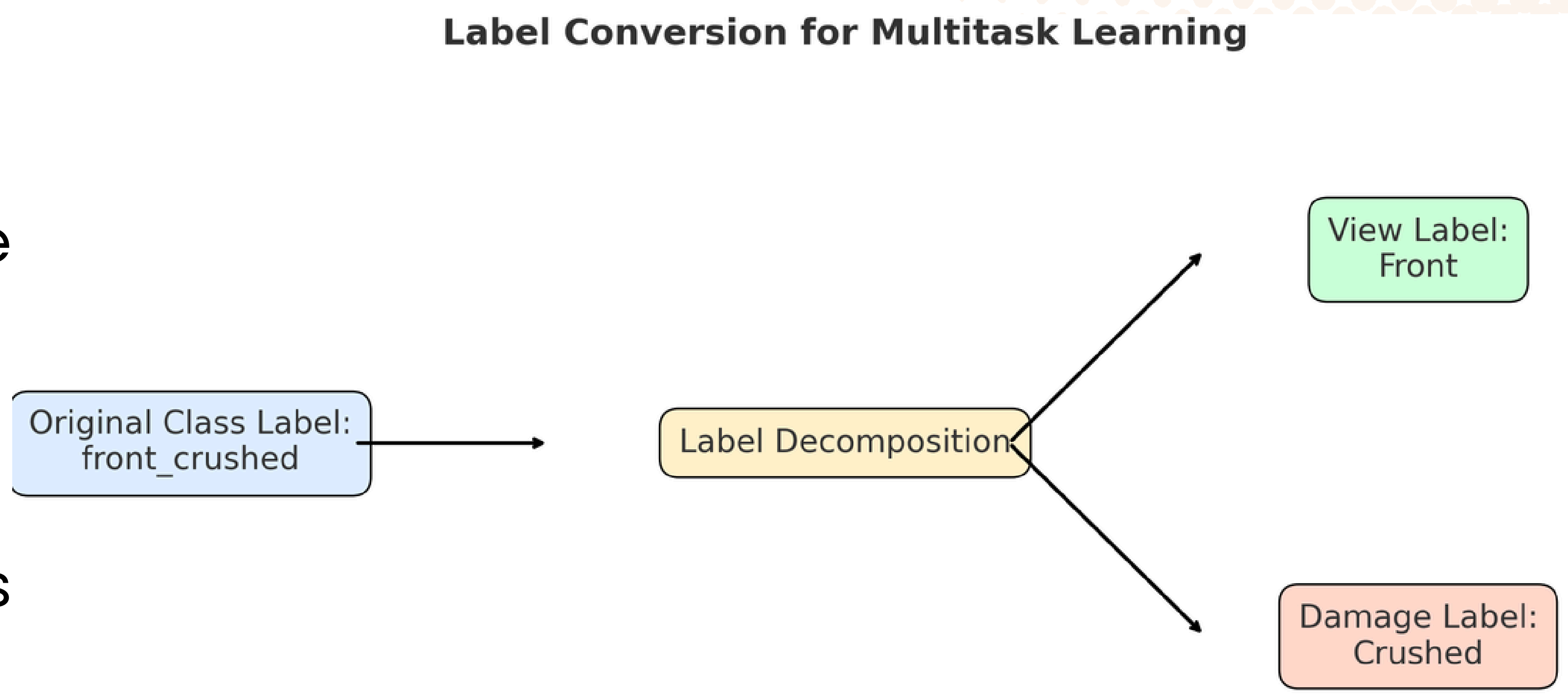
In the initial structure of the dataset, each sample was assigned a single combined class label.
For instance, the label front_crushed simultaneously represented both the viewing angle and the type of damage.

To enable a multitask learning framework, these composite labels were restructured into two separate target variables:

- View Orientation: Front / Rear
- Damage Type: Normal / Crushed / Breakage

This design allowed the model to learn both tasks concurrently from the same input image.

Compared to conventional single-task classification, this approach enhances modeling flexibility and facilitates knowledge sharing between tasks.



Data Augmentation

Before training, we applied a series of image transformations to improve the model's generalization ability and reduce the risk of overfitting.
Overfitting occurs when a model memorizes the training data too well and fails to perform on unseen data.
To mitigate this, we introduced randomness and variation through data augmentation so that the model could learn more generalized patterns.

For the training set, the following transformations were applied:

- Images were resized to 128x128 pixels
- Random horizontal flips with 50% probability
- Random rotations up to 10 degrees
- Slight variations in brightness, contrast, and saturation using ColorJitter

The validation set was only resized and converted to tensors, ensuring stable and unbiased evaluation.
The dataset was split into 80% training and 20% validation.
Each image was passed through the custom MultiTaskCarDataset class, which provided both the view and damage labels for multitask learning.

MODEL ARCHITECTURES

ResNet50

Loaded with torchvision.models.resnet50 .
Used only feature extractor layers (before avgpool).

The output was directed to two different "head" structures after AdaptiveAvgPool2d:
head_view: 2048 → 128 → 2 (Angle estimation)
head_damage: 2048 → 256 → 3 (Damage estimation)
Both heads: Linear → ReLU → Dropout → Linear

MODEL ARCHITECTURES

DenseNet 121

Based on torchvision.models.densenet121 .
applied global AdaptiveAvgPool2d after features block.

Then defined two separate head structures:
head_view: 1024 → 128 → 2
head_damage: 1024 → 256 → 3
During training, early stopping was applied based on the validation loss to prevent overfitting and to optimize training time.

ResNet50

The model has shown a very high success rate in the task of predicting the vehicle angle (front/back). The 95% accuracy rate shows that the model can clearly distinguish this task. This success is due to the clarity of the structural differences of the vehicles and the ability of the model to learn these differences.

The success of the model in the damage type prediction is at the level of 74%. The best performance in this task was seen in the breakage class. Since the crushed and normal classes have less visually obvious differences, the model was occasionally unstable in these classes. In addition, the imbalance between these classes was another factor limiting the performance of the model.

In general, it can be said that the model is quite successful in distinguishing macro-level differences, but needs more careful improvements in classes based on fine details..

Classification Report: DAMAGE (Normal / Crushed / Breakage)

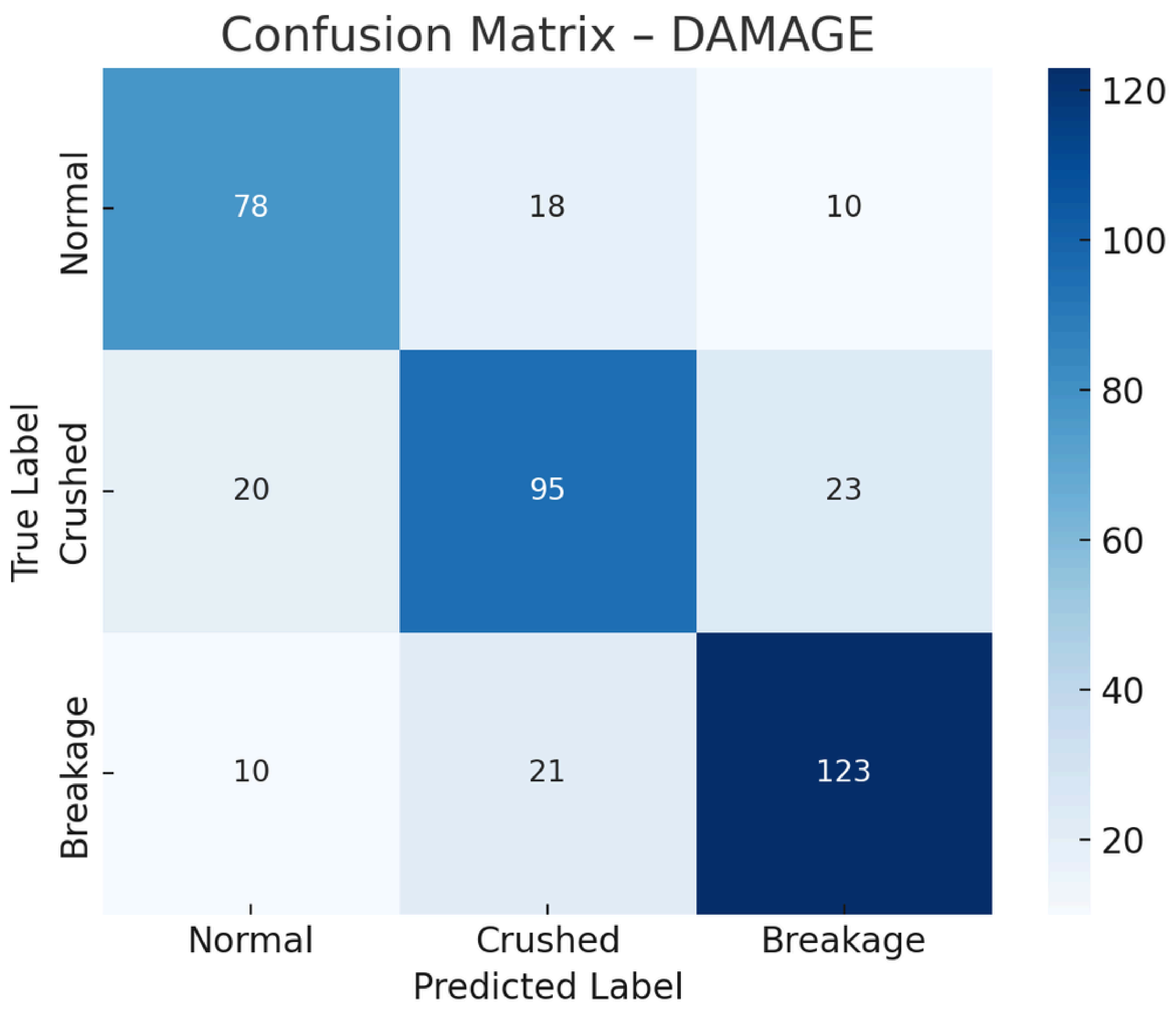
	precision	recall	f1-score	support
Normal	0.68	0.74	0.71	106
Crushed	0.75	0.69	0.72	138
Breakage	0.78	0.80	0.79	154
accuracy			0.74	398
macro avg	0.74	0.74	0.74	398
weighted avg	0.74	0.74	0.74	398

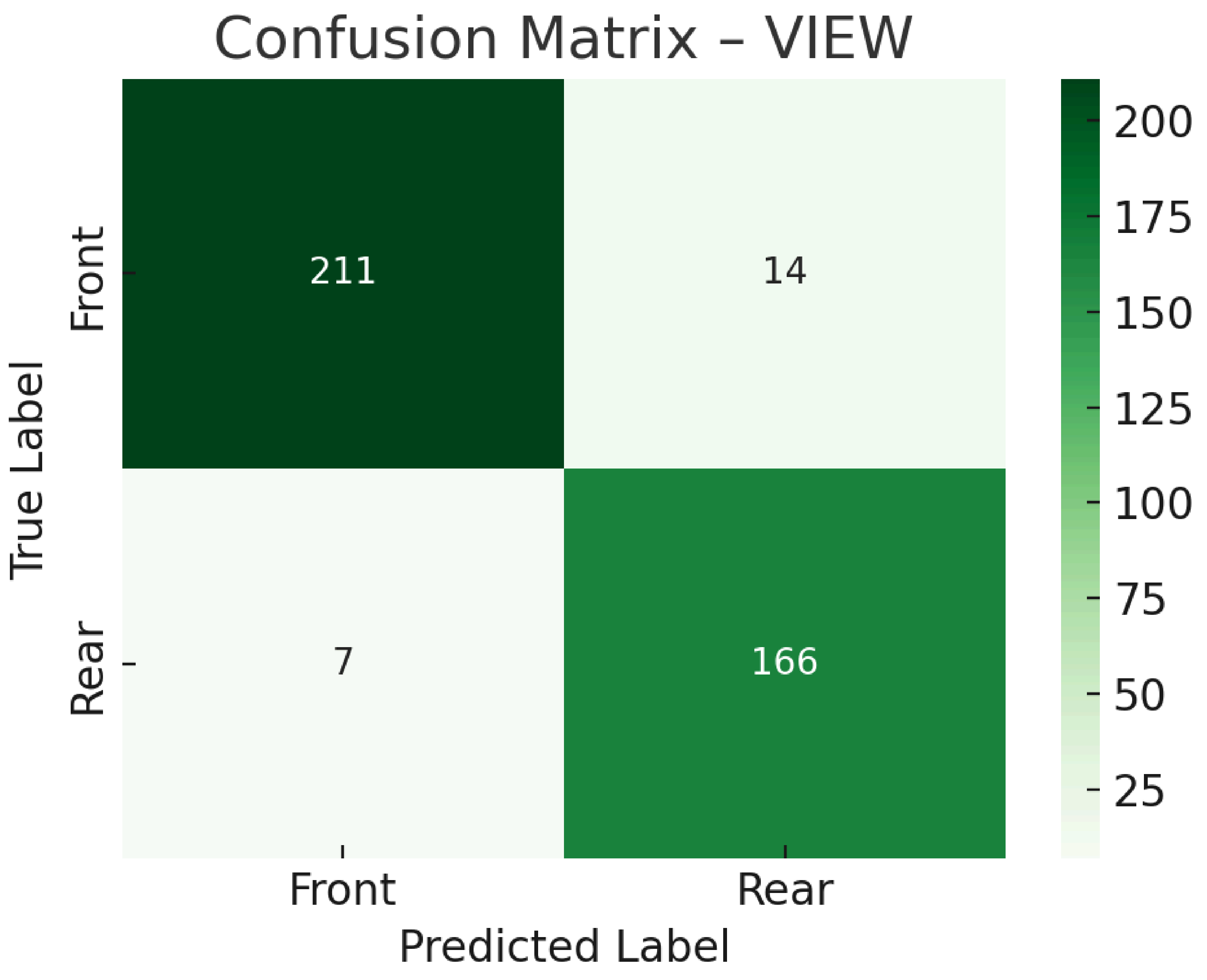
Classification Report: VIEW (Front / Rear)

	precision	recall	f1-score	support
Front	0.96	0.94	0.95	225
Rear	0.95	0.96	0.95	173
accuracy			0.95	398
macro avg	0.95	0.95	0.95	398
weighted avg	0.95	0.95	0.95	398

Confusion Matrices

ResNet50





DenseNet121

The DenseNet121 model has achieved very successful results in the task of predicting vehicle orientation. With an accuracy rate of 98%, the model was able to distinguish front and back angles with high accuracy. This success is based on the ability of DenseNet121 to effectively learn low-level visual details thanks to its dense connections between layers.

In damage type prediction, the model achieved 93% accuracy, especially in the breakage class, it stood out with a 95% f1-score. High success was also achieved in crushed and normal classes. These results show that the model can process visual differences in detail and successfully learn distinguishing features between classes.

In general, the DenseNet121 architecture showed a stable and strong performance in both vehicle orientation and damage type prediction, proving that the model is a very suitable candidate for multi-task classification.

🔧 **Classification Report: DAMAGE (Normal / Crushed / Breakage)**

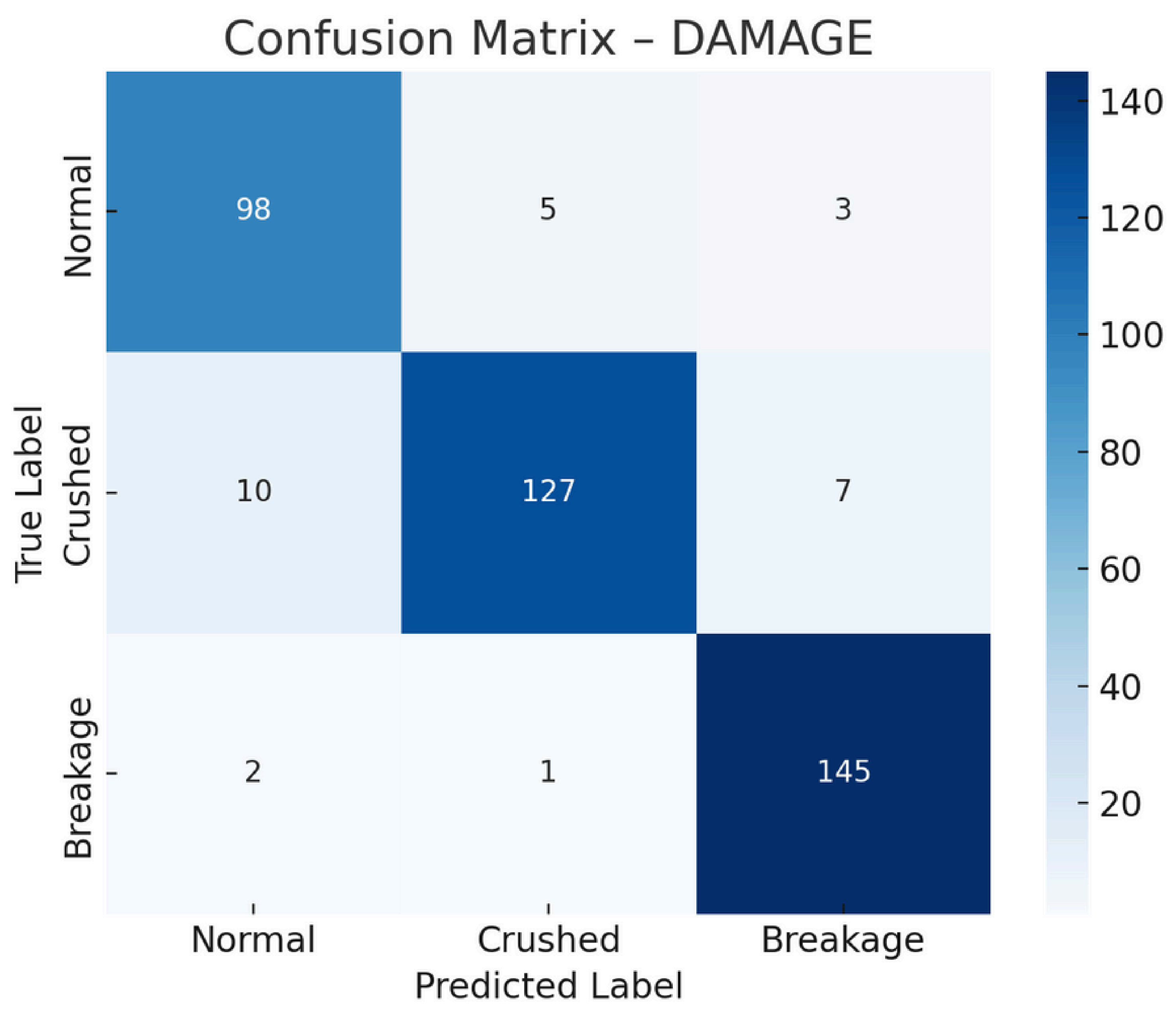
	precision	recall	f1-score	support
Normal	0.93	0.92	0.93	106
Crushed	0.94	0.88	0.91	144
Breakage	0.92	0.98	0.95	148
accuracy			0.93	398
macro avg	0.93	0.93	0.93	398
weighted avg	0.93	0.93	0.93	398

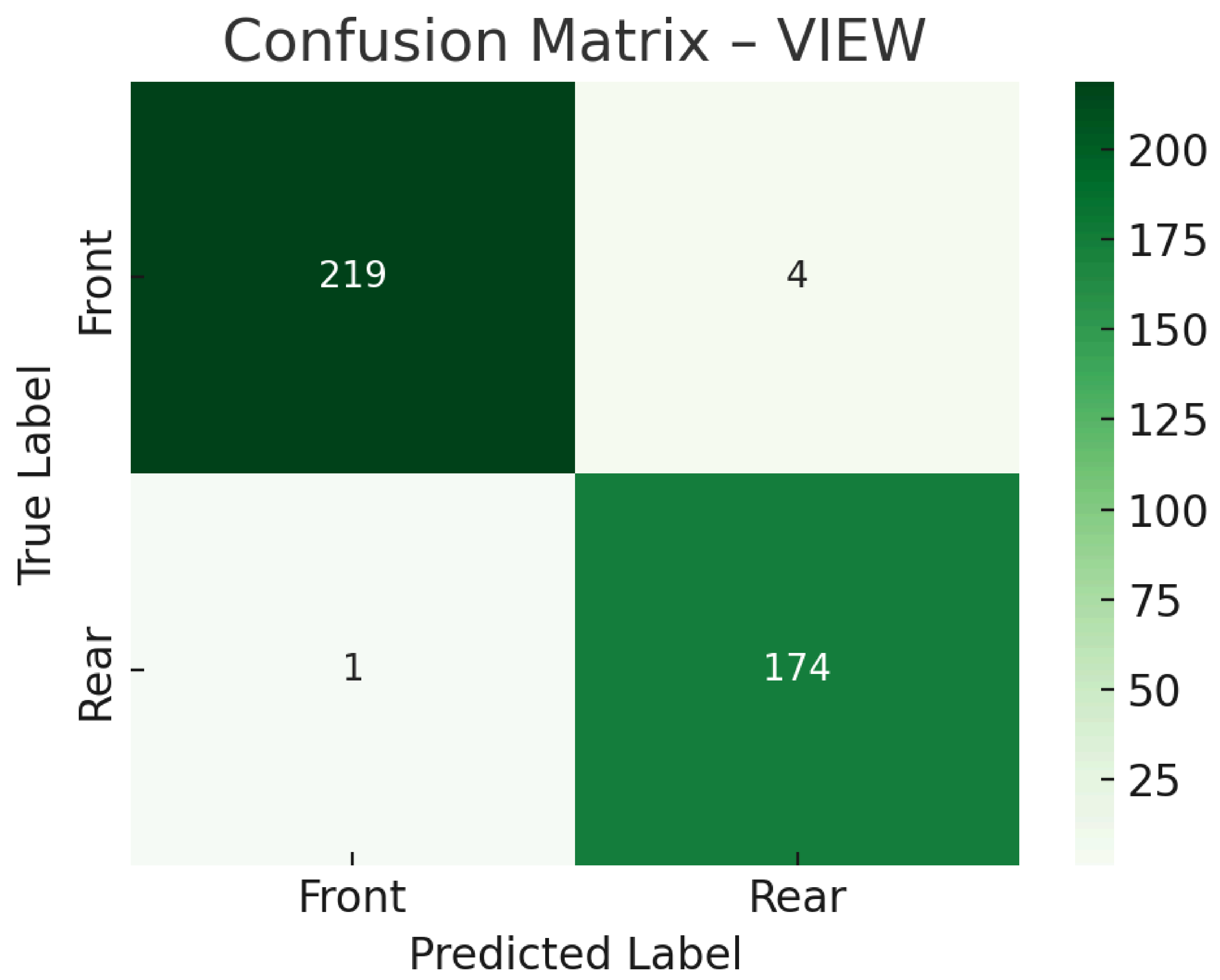
🔧 **Classification Report: VIEW (Front / Rear)**

	precision	recall	f1-score	support
Front	0.97	0.98	0.98	223
Rear	0.98	0.97	0.98	175
accuracy			0.98	398
macro avg	0.98	0.98	0.98	398
weighted avg	0.98	0.98	0.98	398

Confusion Matrices

DenseNet 121

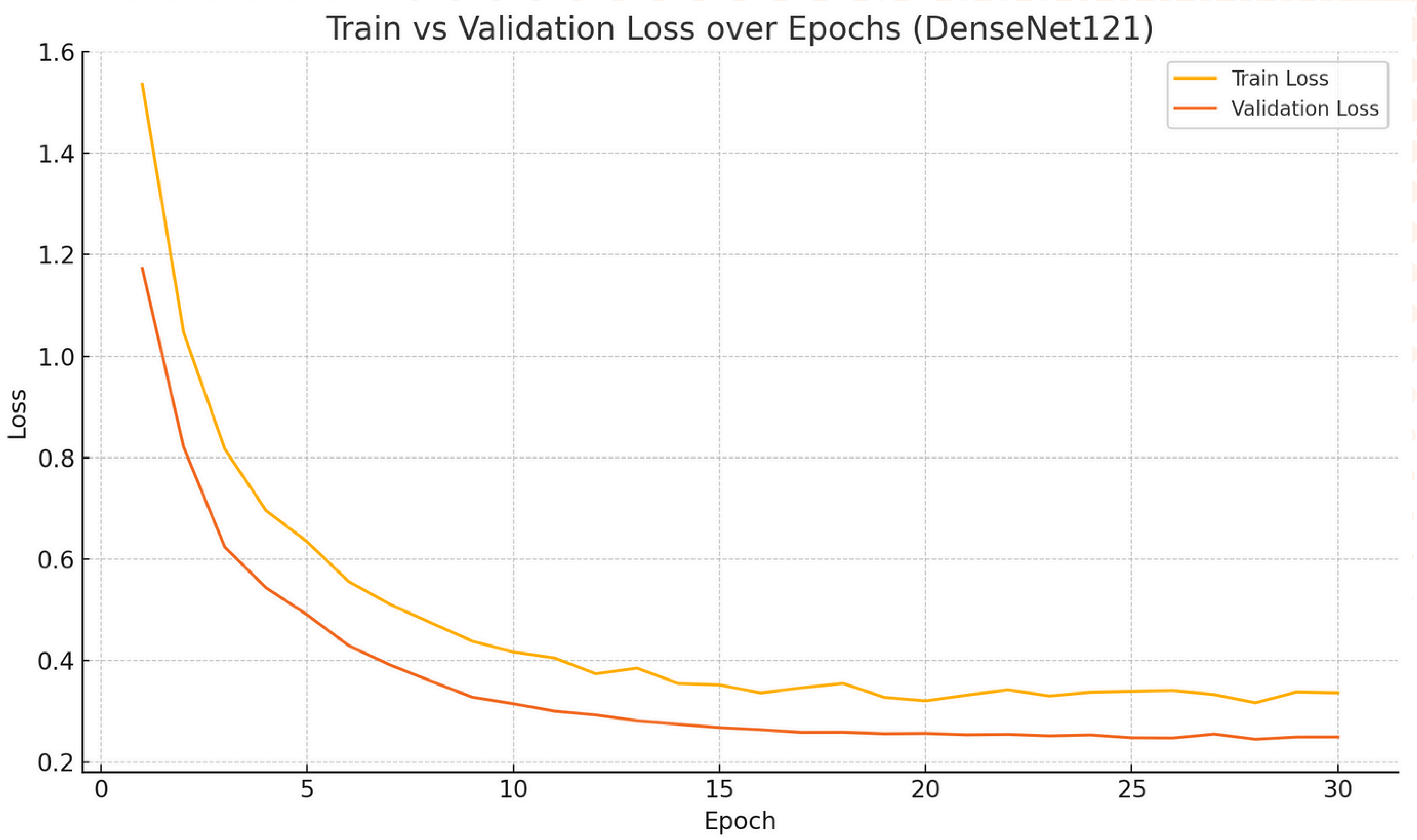




Train vs Validation Loss

DenseNet 121

The graph shows a steady decrease in both training and validation loss, indicating effective learning. The close alignment between the two curves suggests that the model generalizes well without significant overfitting.



Thank you for listening