UNIVERSITÉ Concordia UNIVERSITY

Animal Species Classification

Presentation by Group H

Pooya Khoshabi **40163944**
Pouria Pirian **40207625**
Salar Nasr Azadani **40067490**
Shahzaib Malik **40185011**

Problem Statement

Practical Applications:

- Wildlife monitoring
- Veterinary diagnosis
- Agriculture

Challenges:

- large number of animal species with different features
- variations in the image quality, lighting, and background

Objective

- Manual classification of animal species is a time-consuming and labor-intensive task which makes it difficult to rely on humans for accurate classification of animals.

- Objective of animal species classification is to leverage the power of computer vision to accurately and efficiently identify different types of animals in a range of different applications.

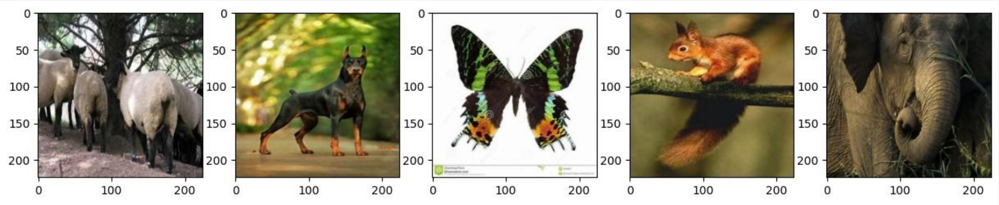
- Our aim is to conduct a comprehensive analysis of the trained models with various architectures on multiple datasets for the task of animal image classification.

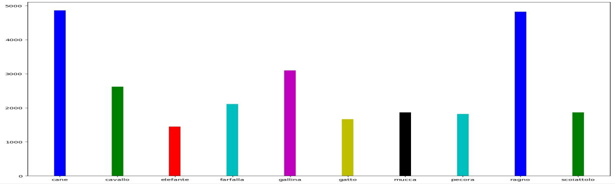
Dataset

Table: Specifications of Datasets

Dataset	# of classes	# of images	Size	Standard Deviation	Balanced
Animal10	10	26,000	614MB	0.2139	No
Animal90	90	5,400	688MB	0.2041	Yes
DogsAndCats	2	10,000	455MB	0.2226	Yes

- Splitting dataset 8:2
  - ❑ training:testing
- Splitting training dataset 8:2
  - ❑ training:validation





Methodology

- Image preprocessing was done before training the models which included the steps:
  - Data Augmentation
  - Normalization
  - Resizing
- Architectures such as ResNet-18, MobileNet V2, and ShuffleNet V2 were used to train the models.

Table 2. Average time needed for one epoch of training

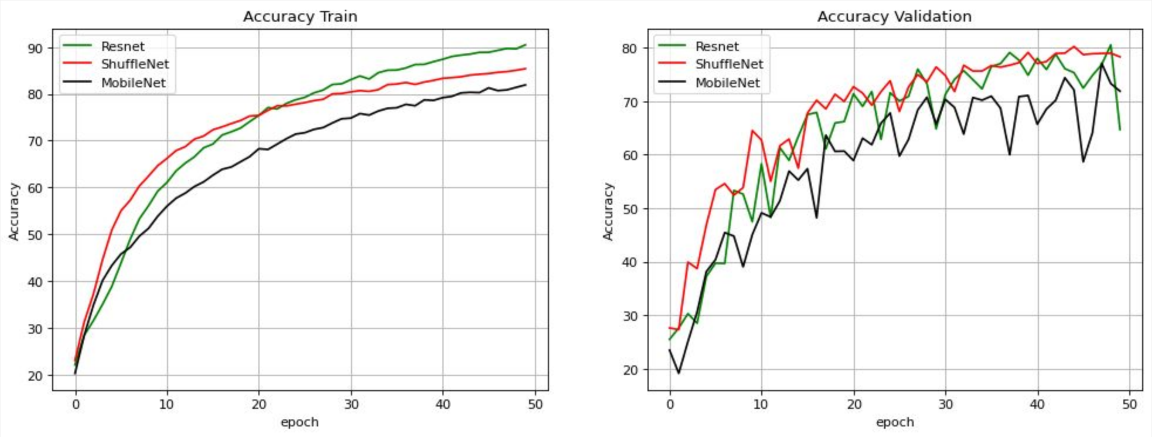
Attributes	Animal10	Animal90	DogsAndCats
ResNet-18	245s	117s	152s
ShuffleNet V2	214s	86s	127s
MobileNet	223s	90s	135s

Experiment Setup (continued)

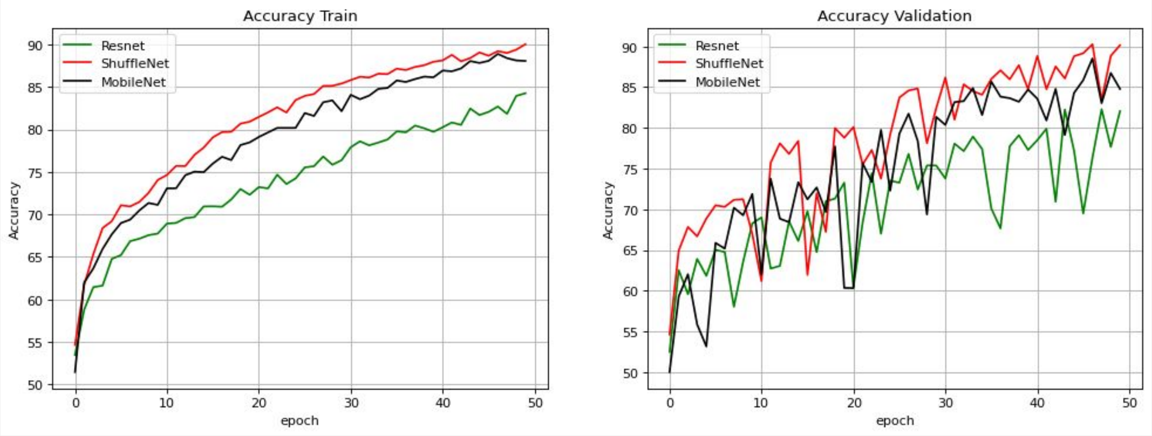
- Models were trained using PyTorch with identical hyper-parameter values.
- The size of the image as input was **224x224**
- Batch size was set to **128** images per epoch
- Learning rate was set to **0.01**
- Models were trained on 50 epochs
- CrossEntropyLoss was used as loss function
- ADAM optimization algorithm

Results

Animal10:



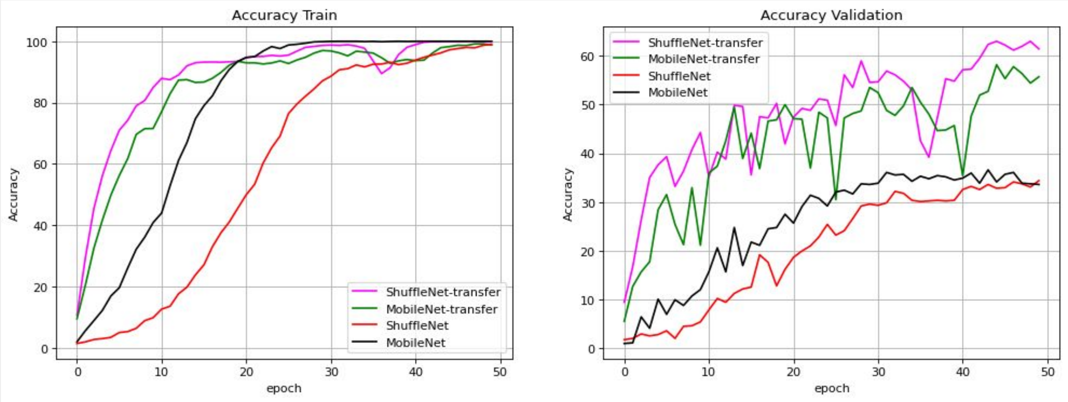
DogsAndCats:



Results (Transfer Learning)

- The effect of Transfer Learning is provided below:

Animal90:



- The result of hyperparameter tuning is provided below: (ShuffleNet and Animal10)

Learning rate	0.1	0.01	0.001	0.0001	0.005	0.0005
Accuracy val after 10 epochs	18.99%	59.54%	59.91%	37.32%	61.84%	57.49%

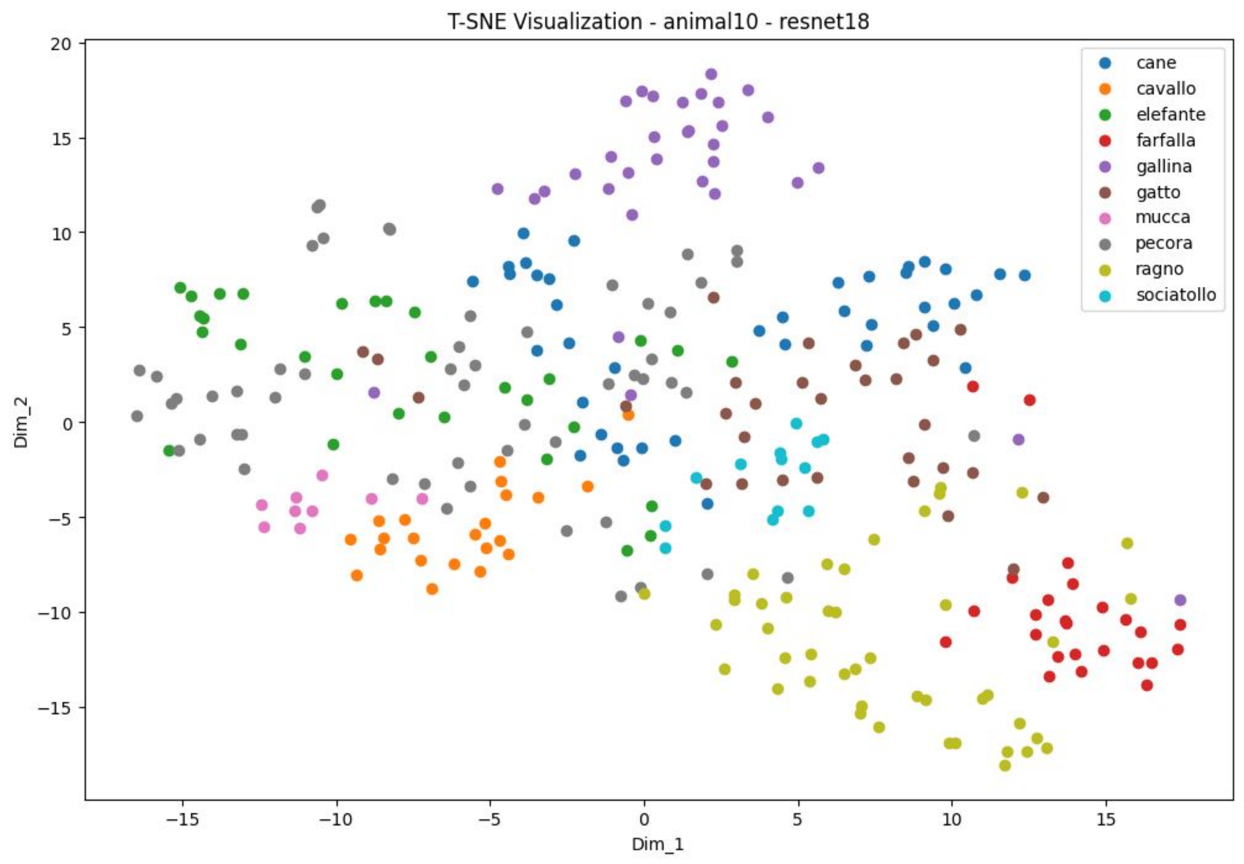
Results (On test dataset)

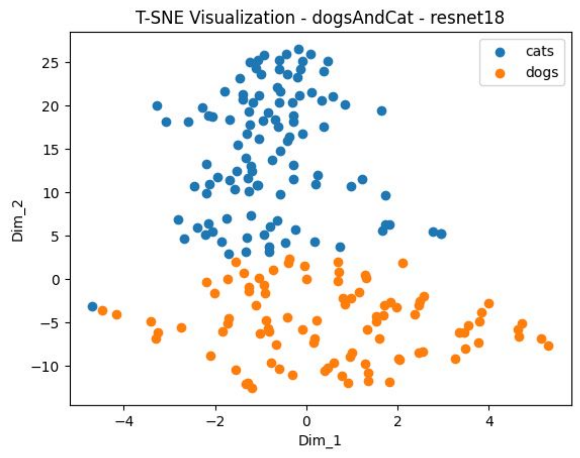
Models and Dataset			
	Animal 10	**Animal 90**	**Dogs and Cats**
ResNet 18	65.32%	41.01%	80.88%
ShuffleNet V2	77.87%	36.81%	89.63%
MobileNet V2	72.20%	33.69%	85.15%

Transfer Learning	
	Animal 90
SuffleNet V2	66.01%
MobileNet V2	51.85%

Fine-Tuning Hyperparameter	
ShuffleNet V2	**Animal 10**
lr = 0.01	77.87%
lr= 0.005	78.43%

Results (TSNE)





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