

Project Report: Cat vs. Dog Classification Using Pre-trained MobileNetV2

Author: Syed Rahmath Ullah Hussaini

Guide: Dr. Ahmed Rimaz Faizabadi

Institution: Delloyd R&D

1. Introduction

This project focuses on using a pre-trained deep learning model to classify images of cats and dogs.

Instead of training a model from scratch, we leverage MobileNetV2, a lightweight convolutional neural network pre-trained on ImageNet, which contains 1,000 classes including various cat and dog breeds.

The goals are:

1. Classify a set of images into cats or dogs.
 2. Identify misclassified images and analyze reasons for inaccuracy.
 3. Demonstrate practical use of transfer learning for image classification.
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2. Dataset

The dataset is organized as follows:

sample_images/

├─ train/

| ├─ cats/

| └─ dogs/

└─ validation/

├─ cats/

└─ dogs/

- Training and validation directories contain labeled images of cats and dogs.

- The script randomly samples 50 images for testing and evaluation.
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3. Methodology

3.1 Model Selection

- MobileNetV2 was chosen due to its efficiency and pre-training on ImageNet.
- Pre-trained weights allow feature extraction without requiring extensive data or GPU resources.

3.2 Image Preprocessing

- Images are resized to 224x224 pixels to match MobileNetV2 input requirements.
- Pixel values are normalized using `preprocess_input` from `tensorflow.keras.applications.mobilenet_v2`.

3.3 Prediction Simplification

- MobileNetV2 predicts 1,000 classes.
- We simplify predictions to:
 - cat if the top prediction contains keywords like "cat", "tabby", "siamese".
 - dog if the top prediction contains "dog", "retriever", "poodle", "husky".
 - unknown if the prediction does not match the keywords.

3.4 Evaluation

- Predictions are compared against ground truth labels.
 - Misclassified images, particularly dogs misclassified as other breeds, are recorded for analysis.
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4. Results

4.1 Classification Summary

Image Name	True Label	Predicted Label	Top-1 Label
dog1.jpg	dog	dog	Labrador_retriever
dog2.jpg	dog	unknown	Basset
cat1.jpg	cat	cat	tabby
cat2.jpg	cat	cat	Siamese

Out of 50 tested images, cats were classified with high accuracy, while some dogs were misclassified due to breed-specific predictions in ImageNet.

4.2 Misclassified Dogs

Image Name	Predicted Label	Reason
dog2.jpg	unknown	Model predicted a breed not mapped to "dog"
dog5.jpg	unknown	Model predicted "Brittany_spaniel", simplified to unknown

Observation:

MobileNetV2 does not explicitly predict "dog" for all breeds. This leads to inaccurate simplification when mapping breed labels to the binary category.

5. Analysis and Discussion

1. Strengths

- Efficient classification using pre-trained weights.
- High accuracy for cats due to distinctive features (e.g., tabby stripes, Siamese face shapes).
- Quick and requires minimal computational resources.

2. Limitations

- Misclassification of dogs due to ImageNet's multiple breed categories.
- Simplification logic cannot cover all possible dog breeds.

- Binary classification is not ideal with a model trained for 1,000-class prediction.

3. Suggestions for Improvement

- Fine-tune MobileNetV2 on a binary cat-vs-dog dataset.
 - Include a more comprehensive mapping of dog breeds to the "dog" category.
 - Use ensemble models or thresholding on multiple top predictions.
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6. Visual Results

- results_classification.png & results_classification2.png: Visualization of correct vs. misclassified images.
- misclassified_dogs.png: Example dog images misclassified by the model.
- reason_For_inaccuracy.png: Diagram showing why misclassification occurs.

These visualizations help identify patterns in misclassification and provide insights for model improvement.

7. Conclusion

- Pre-trained MobileNetV2 can effectively classify cats but struggles with dogs due to breed-specific predictions.
- Binary classification with multi-class models requires careful post-processing or fine-tuning.
- This experiment demonstrates the practical use of transfer learning, the importance of data preprocessing, and the need for task-specific model adaptation.

Key takeaway:

While pre-trained models provide a strong starting point, task-specific fine-tuning is crucial for high-accuracy binary classification.

8. References

1. TensorFlow Keras Applications – MobileNetV2:
https://www.tensorflow.org/api_docs/python/tf/keras/applications/MobileNetV2

2. ImageNet Dataset: <http://www.image-net.org/>
3. Keras Image Preprocessing Documentation:
https://www.tensorflow.org/api_docs/python/tf/keras/preprocessing/image