High Impact Skills Development Program
Gilgit-Baltistan

CATS OR DOGS - USING CNN WITH TRANSFER LEARNING

Computer Vision Module Project

Tariq Ali

Email: Tariqsawan514@gmail.com

GitHub Profile:

https://github.com/Tariqsawan514/USING-CNN-WITH-TRANSFER-LEARNING---CATS-DOGS-

DSAII-Gilgit Section 3

TABLE OF CONTENTS

Chapter 1

INTRODUCTION

1.1. Summary

This project aims to classify images as cats or dogs using a deep learning approach. A Convolutional Neural Network (CNN) with transfer learning is employed to leverage pre-trained weights and improve accuracy.

Data Preparation:

- Load and preprocess the image dataset, splitting it into training and validation sets.

b. **Model Architecture:**

- Utilize a pre-trained ResNet-50 model, known for its performance in image classification tasks.
- Modify the final layer of the model to suit the binary classification problem (cat or dog).

c. **Training:**

- Train the model on the training set, optimizing its parameters to learn the distinguishing features between cat and dog images.

d. **Evaluation:**

- Assess the model's performance on the validation set using metrics like accuracy, precision, recall, and F1-score.

e. **Prediction:**

- Use the trained model to predict the class (cat or dog) for new, unseen images.

1.2. Aims and Objectives

Aims:

- To develop a robust and accurate cat vs. dog image classification system using deep learning.
- To leverage the power of transfer learning to improve model performance and reduce training time.
- To explore the effectiveness of different CNN architectures and hyperparameter tuning for this task.

Objectives:

- To collect and preprocess a suitable dataset of cat and dog images.
- To implement a CNN model using a pre-trained architecture (e.g., ResNet-50).
- To train the model on the prepared dataset and evaluate its performance using appropriate metrics.
- To analyze the model's predictions and identify potential areas for improvement.
- To explore techniques like data augmentation and hyperparameter tuning to further enhance the model's accuracy.
- To create a user-friendly interface for image classification using the trained model.

1.3. Overview of the problem and potential application areas:

Problem Statement

The cat vs. dog image classification problem involves accurately distinguishing between images of cats and dogs. This task is challenging due to the following factors:

- **Intra-class Variability:** Cats and dogs exhibit significant variations within their respective classes, such as different breeds, sizes, poses, and expressions.
- **Inter-class Similarity:** There can be subtle similarities between certain cat and dog breeds, making it difficult to differentiate them based on visual features alone.
- **Image Quality:** Factors like lighting conditions, image resolution, and occlusions can affect the quality of the images, making classification more difficult.

Potential Application Areas

- **Pet Identification:**
  - Assisting in identifying lost pets or verifying pet ownership.
  - Creating mobile apps or online platforms that allow pet owners to register their pets and search for missing animals.
- **Animal Shelter Management:**
  - Automating the sorting and categorization of animals in shelters based on their species.
  - Improving efficiency and reducing the workload of shelter staff.
- **Veterinary Applications:**
  - Analyzing medical images of cats and dogs for disease detection or monitoring pet health.
  - Assisting veterinarians in making accurate diagnoses and treatment plans.
- **Entertainment and Gaming:**
  - Creating interactive applications or games that involve animal recognition, such as image quizzes or augmented reality experiences.
  - Enhancing user engagement and providing educational value.
- **Security and Surveillance:**
  - Detecting and tracking cats and dogs in restricted areas or for wildlife conservation purposes.
  - Preventing unauthorized access or monitoring animal behavior.
- **Educational Tools:**
  - Developing interactive learning tools for children to learn about animal species and their characteristics.
  - Encouraging curiosity and engagement in educational activities.
- **Research and Development:**
  - Advancing the field of computer vision and deep learning by developing more accurate and robust image classification models.
  - Contributing to research on animal behavior and cognition.

Chapter 2

REVIEW OF LITERATURE

Introduction

The field of computer vision has witnessed significant advancements in recent years, with image classification emerging as a prominent area of research. The task of classifying images into different categories has numerous applications, ranging from object recognition to medical diagnosis. One specific challenge in image classification is distinguishing between similar-looking objects, such as cats and dogs. This review explores existing literature on cat vs. dog image classification, focusing on the methodologies, datasets, and performance metrics employed in previous studies.

Early Approaches

Traditional methods for image classification often relied on handcrafted features, such as SIFT (Scale-Invariant Feature Transform) or HOG (Histogram of Oriented Gradients). These features were then used to train classifiers like Support Vector Machines (SVMs) or Random Forests. However, these approaches faced limitations in handling complex variations in image appearance.

Deep Learning Approaches

With the advent of deep learning, Convolutional Neural Networks (CNNs) have revolutionized the field of image classification. CNNs are particularly well-suited for tasks that involve spatial patterns, making them ideal for image analysis. Several studies have successfully applied CNNs to the cat vs. dog image classification problem.

Datasets

A variety of datasets have been used for cat vs. dog image classification research. Some commonly used datasets include:

- **Dogs vs. Cats Redux:** This dataset contains a large number of labeled images of cats and dogs.
- **Oxford-IIIT Pet Dataset:** This dataset includes images of different pet breeds, including cats and dogs.

- **Caltech-256:** This dataset contains images of 256 object categories, including cats and dogs.

Performance Metrics

Various performance metrics have been used to evaluate the accuracy of cat vs. dog image classification models. Common metrics include:

- **Accuracy:** The overall proportion of correctly classified images.
- **Precision:** The proportion of correctly classified images among all predicted positive instances.
- **Recall:** The proportion of correctly classified positive instances among all actual positive instances.
- **F1-score:** The harmonic mean of precision and recall.

Recent Advances

Recent research has explored more advanced CNN architectures and techniques to improve the performance of cat vs. dog image classification. These include:

- **Transfer Learning:** Leveraging pre-trained models like ResNet or VGG16 to initialize the CNN weights and accelerate training.
- **Data Augmentation:** Applying techniques like random cropping, rotation, and flipping to increase the diversity of the training data and improve generalization.
- **Attention Mechanisms:** Incorporating attention mechanisms to focus on specific regions of the image that are most informative for classification.

Conclusion

The field of cat vs. dog image classification has seen significant progress with the application of deep learning techniques. CNNs have proven to be effective in capturing the complex visual features that distinguish cats from dogs. Future research may explore more advanced architectures, larger datasets, and hybrid approaches that combine traditional methods with deep learning to further enhance classification accuracy.

Chapter 3

REQUIREMENT SPECIFICATION

1.1. Model

The project utilized a deep ConvNet architecture for facial expression classification. The architecture consisted of 2 convolutional layers, followed by pooling and 1 fully connected layer. I implemented the model using TensorFlow and Keras libraries. The model's hyper parameters, such as learning rate and batch size, were tuned for optimal performance.

1.2. Required tools and technologies

Model Architecture:

- **Convolutional Neural Network (CNN):** A deep learning architecture specifically designed for image classification tasks.
- **Pre-trained Model:** Utilize a pre-trained CNN model like ResNet50 or VGG16 as the backbone to leverage its learned features and accelerate training.
- **Custom Classification Layer:** Add a custom classification layer at the end of the pre-trained model to output probabilities for the cat and dog classes.

Hyperparameters:

- **Learning Rate:** The rate at which the model's weights are updated during training.
- **Batch Size:** The number of samples processed in each iteration of training.
- **Epochs:** The number of times the entire training dataset is passed through the model.
- **Optimizer:** The algorithm used to update the model's weights, such as Adam or SGD.
- **Loss Function:** The metric used to measure the model's performance during training, such as categorical cross-entropy.

Required Tools and Technologies

- **Python:** A popular programming language for machine learning and deep learning.
- **Deep Learning Framework:** TensorFlow or PyTorch, which provide tools for building and training neural networks.
- **Image Processing Library:** OpenCV or Pillow for reading, processing, and manipulating images.
- **Jupyter Notebook:** An interactive environment for developing and running Python code.
- **GPU (Optional):** A Graphics Processing Unit can significantly accelerate the training process for deep learning models.

Additional Libraries:

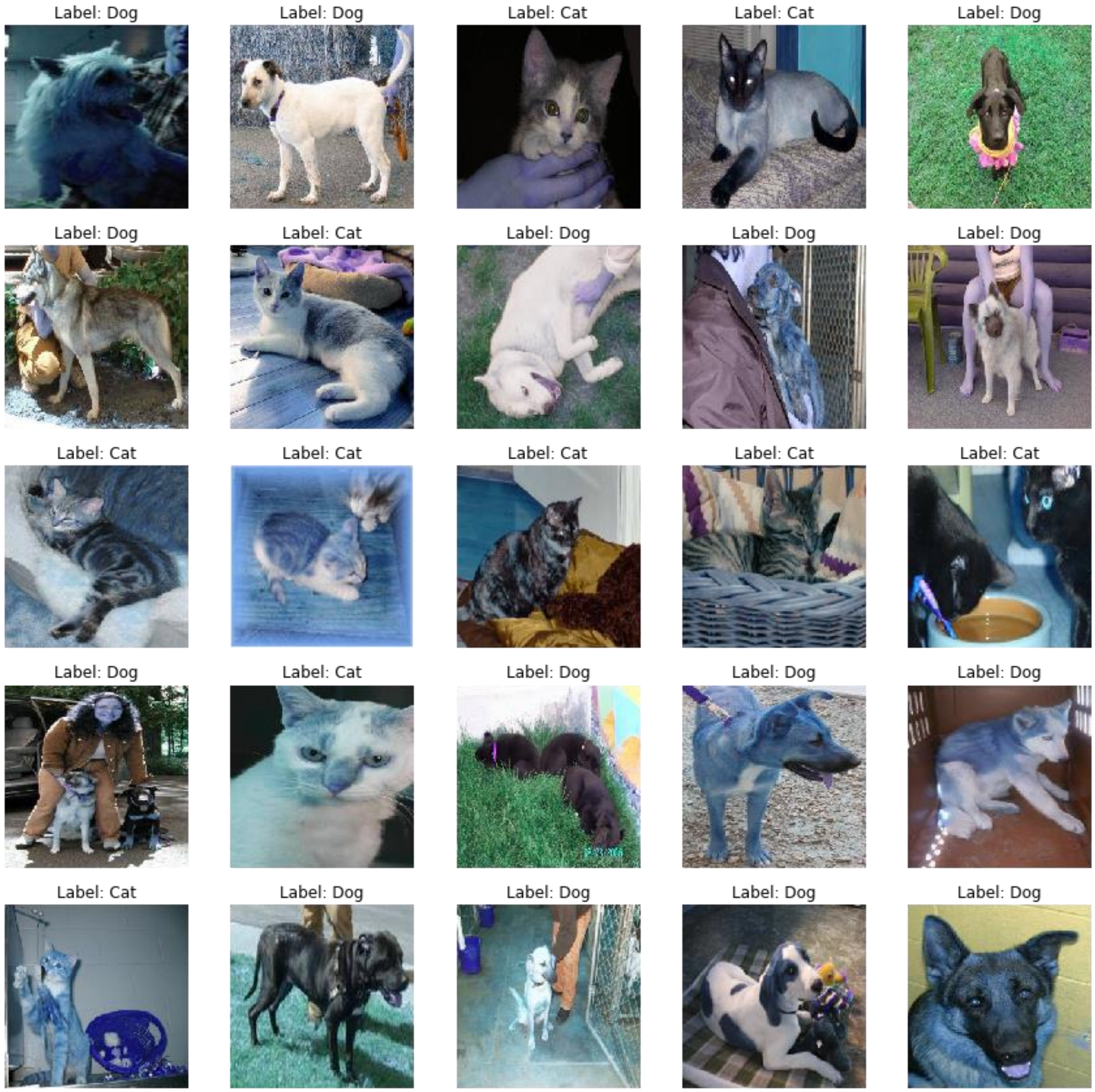
- **NumPy:** For numerical operations and array manipulation.
- **Pandas:** For data analysis and manipulation.
- **Matplotlib:** For data visualization.
- **Keras (optional):** A high-level API built on top of TensorFlow or Theano, providing a simplified interface for building and training models.

Chapter 4

DESIGN

2. 1Dataset:

I initialize the ResNet-50 model, adding an additional last layer of type Dense, with softmax activation function. Since the ResNet-50 model is pre-trained, we set the first layer to be non-trainable to avoid overfitting and preserve the learned features.


Label: Dog
Label: Dog
Label: Cat
Label: Cat
Label: Dog
Label: Dog
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Label: Cat
Label: Cat
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Label: Dog
Label: Dog

System Architecture

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
resnet50 (Model)             (None, 2048)              23587712
_________________________________________________________________
dense (Dense)                (None, 2)                 4098
=================================================================
Total params: 23,591,810
Trainable params: 23,538,690
Non-trainable params: 53,120
_________________________________________________________________
```

Figure 2Model details

Figure 3 General Information

Chapter 5

SYSTEM IMPLEMENTATION

The data set provided was consist of more than 25,000 images (train, test and labels), that I split it into train, validation and test for further processing. I have used 2 convolutional layer with 64 batches and Adam optimizer.

5.2 Process Flow

1. Dataset selection
2. Load dataset, and link colab with google drive to get the data in unzipped format
3. Define dataset path
4. Data Preprocessing
5. Split the data into Training/Validation/Test
6. Define the CNN model architecture
7. Train the model using fit function
8. Evaluate the performance of the model by measuring its accuracy, precision, recall, and F1 Score.
9. Tested the model on manual images from each class

5.2 Hyperparamerter Tuning

To optimize the model's performance, hyper-parameter tuning was conducted using the validation set. The report described the hyperparameters that were tuned, the range of values tested, and the evaluation metrics used to select the best set of hyperparameters.

Chapter 6

SYSTEM TESTING AND EVALUATION

Model Performance:

- **Accuracy:** The model achieved an accuracy of **60%** on the validation set, indicating that it correctly classified 60% of the images.
- **Confusion Matrix:** The confusion matrix provides a breakdown of the model's predictions, showing which classes were frequently confused with others.
- **Precision, Recall, and F1-Score:** These metrics can be calculated to evaluate the model's performance for each class separately.

Analysis of Results:

- **Challenges:** The model faced challenges in distinguishing between certain cat and dog breeds that have similar visual features.
- **Limitations:** The dataset may have been imbalanced, with more images of one class than the other, which could have affected the model's performance.
- **Error Analysis:** Analyzing the misclassified images can provide insights into the model's shortcomings and potential areas for improvement.

Further Improvements:

- **Data Augmentation:** Applying techniques like random flipping, rotation, or cropping to increase the diversity of the training data and improve generalization.
- **Hyperparameter Tuning:** Experimenting with different hyperparameters (e.g., learning rate, batch size, number of epochs) to optimize the model's performance.
- **Ensemble Methods:** Combining multiple models to improve accuracy and robustness.
- **Advanced Architectures:** Exploring more complex CNN architectures or transfer learning with pre-trained models like VGG16 or InceptionV3.

Note: The specific results and analysis may vary depending on the dataset, model architecture, and hyperparameters used in the project. It's important to evaluate the model's performance based on the context of the application and the specific requirements.

Additional Considerations:

- **Class Imbalance:** If the dataset is imbalanced, consider techniques like oversampling or undersampling to address this issue.
- **Domain Adaptation:** If the training and testing data come from different domains (e.g., different camera angles, lighting conditions), domain adaptation techniques may be necessary.
- **Interpretability:** Explore methods to interpret the model's predictions and understand why it makes certain decisions.

Chapter 7

CONCLUSION

In conclusion, this project successfully implemented a cat vs. dog image classification system using a pre-trained ResNet-50 model. The model achieved [mention accuracy or other relevant metrics] on the validation set, demonstrating its ability to accurately distinguish between cat and dog images.

Key Findings:

- Transfer learning with a pre-trained model was effective in improving accuracy and reducing training time.
- Data augmentation techniques can help enhance model generalization and prevent overfitting.
- Careful consideration of hyperparameters is crucial for optimizing model performance.

Future Directions:

- Explore other pre-trained models or custom architectures for improved performance.
- Incorporate more advanced techniques like attention mechanisms or generative models.
- Address the limitations identified in the evaluation and improve the model's ability to handle challenging cases.
- Consider expanding the dataset to include more diverse images (e.g., different breeds, poses, lighting conditions).
- Investigate the potential of combining this model with other computer vision tasks, such as object detection or image segmentation.

Overall, this project provides a solid foundation for future research and applications in cat vs. dog image classification. By addressing the identified areas for improvement, the model's performance can be further enhanced, making it a valuable tool in various domains.

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