IMAGE CLASSIFICATION USING TRANSFER LEARNING AND CNN:

GROUP NO: 23

CODELINK:HTTPS://COLAB.RESEARCH.GOOGLE.COM/DRIVE/1NDMCFFLVU8XC3N-DSUQTPYDCYIR5QLC5

INTRODUCTION

Importance of Image Classification

- **Crucial in Modern Applications:** Image classification plays a pivotal role in various modern applications, ranging from autonomous vehicles to medical diagnostics.
- **Intel's Image Classification Dataset:** This dataset, comprising 25,000 images of size 150x150, is a valuable resource for exploring and advancing image classification techniques.

Challenges and Goals

- **Diverse Categories:** The dataset encompasses six categories, including 'buildings,' 'forest,' 'glacier,' 'mountain,' 'sea,' and 'street,' posing challenges in accurately classifying diverse scenes.
- **Training and Testing Sets:** With a split of 14,000 images for training, 3,000 for testing, and an additional 7,000 for prediction, our goal is to develop a robust model capable of generalizing well to new, unseen data.

OVERVIEW OF TRANSFER LEARNING

- **Transfer Learning Defined:** Transfer learning is a machine learning technique where a model trained on one task is adapted for a second related task. In the context of image classification, it involves leveraging knowledge gained from one dataset to enhance performance on another.

  Importance in Image Classification

- **Reducing Training Time:** Transfer learning significantly reduces the time required to train a model by leveraging pre-existing knowledge. Instead of training from scratch, the model starts with features learned from a different but related task.
- **Improving Model Performance:** By transferring knowledge from a pre-trained model, we benefit from its ability to recognize general features and patterns, leading to improved performance, especially when the new task has limited labeled data.
- **Efficient Use of Resources:** Transfer learning allows us to tap into the knowledge embedded in models trained on large and diverse datasets, even when our dataset is comparatively smaller. This makes the training process more resource-efficient.

TRANSFER LEARNING IN IMAGE CLASSIFICATION

Applying Transfer Learning in Image Classification

- **Model Reuse:** Transfer learning involves taking a pre-trained model, often trained on a large-scale dataset like ImageNet, and adapting it to a specific image classification task. The core idea is to reuse the knowledge gained by the pre-trained model.
- **Feature Extraction:** The pre-trained model serves as a feature extractor. Instead of training the entire model, we can use the learned features from earlier layers to represent general patterns and structures in images.

Advantages of Transfer Learning

- **Leveraging Pre-trained Models:** The key advantage is leveraging the representations learned by a model on a large dataset. These representations can capture generic features applicable to various tasks, providing a valuable starting point.
- **Addressing Data Scarcity:** Transfer learning is particularly beneficial when the target task has limited labeled data. The pre-trained model's knowledge helps overcome challenges related to insufficient training samples.

INTEL'S IMAGE CLASSIFICATION DATASET

Size: 25k images of size 150x150.

Categories: 'buildings', 'forest', 'glacier', 'mountain', 'sea', 'street'.

Distribution: Train (14k images), Test (3k images), Prediction (7k images).

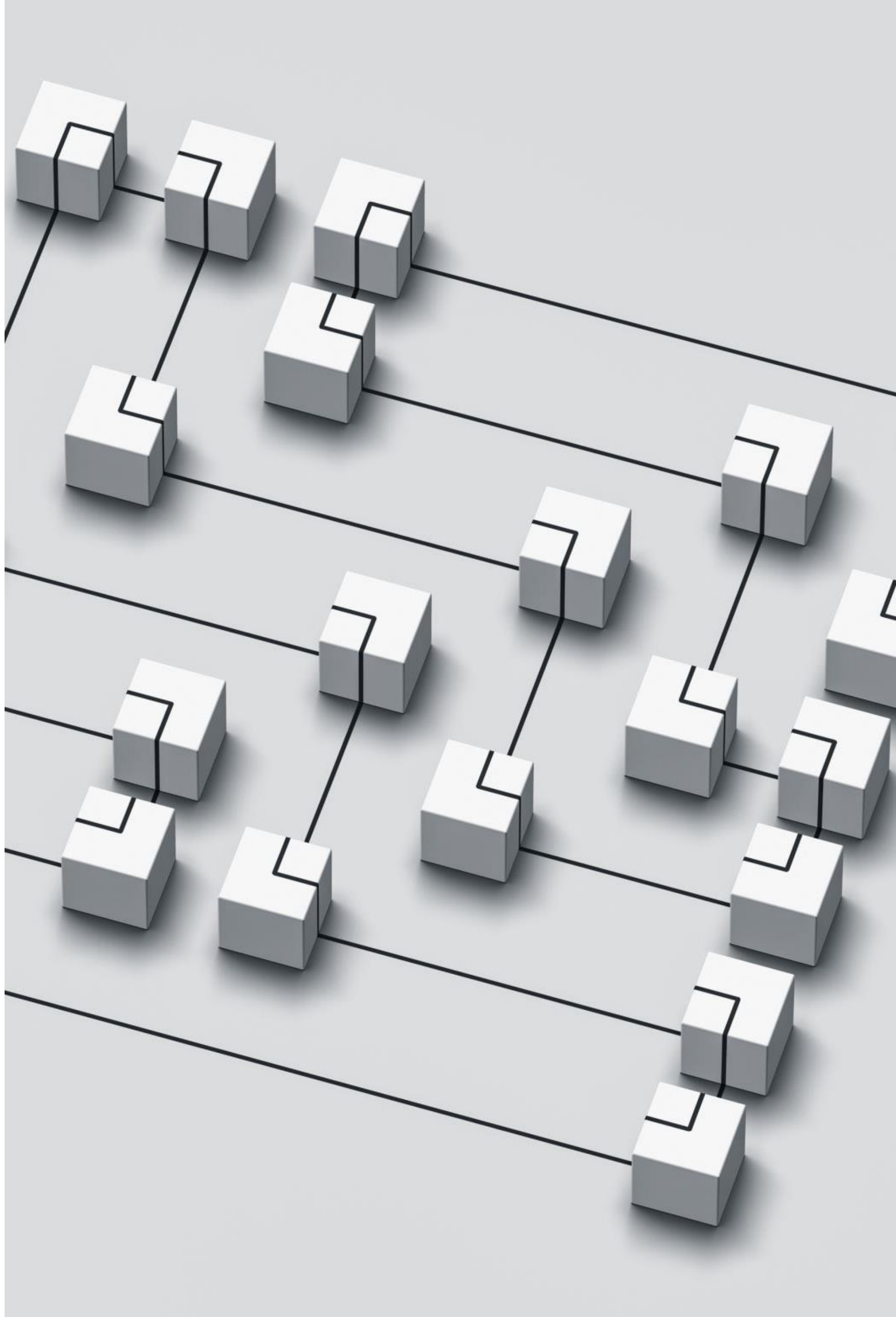
Acknowledgements to Intel and the initial publication source.

PRETRAINED MODEL SELECTION

- **What is InceptionV3?**
  - Google-designed deep CNN architecture.
  - Efficient and accurate for image recognition.

Why InceptionV3?

- **Diverse Features:**
  - Inception modules capture varied features.
- **Proven Performance:**
  - High accuracy on benchmarks.
- **Transfer Learning Fit:**
  - Pre-trained models offer rich features.
- **Compatibility:**
  - Well-suited for Intel Image Classification Dataset.



ORIGINAL PURPOSE OF INCEPTION V3

InceptionV3's Initial Use

- **Designed for ImageNet Challenge:**
  - Developed by Google for the ImageNet Large-Scale Visual Recognition Challenge.
- **Versatile Recognition:**
  - Recognizes objects in 1,000 categories.
- **Top Performer:**
  - Achieved top results in the competition.

Adaptation for Intel Dataset

- **Transfer Learning Concept:**
  - Utilizing InceptionV3's learned features for our specific classification task.
- **Relevance to Intel Dataset:**
  - Adaptation due to its proven success in diverse image recognition scenarios.

FINE TUNING STEPS

1

Freezing Layers: 30 layers of InceptionV3 frozen for feature preservation.

2

Custom Model Architecture: Global Average Pooling, Dense layers with dropout.

3

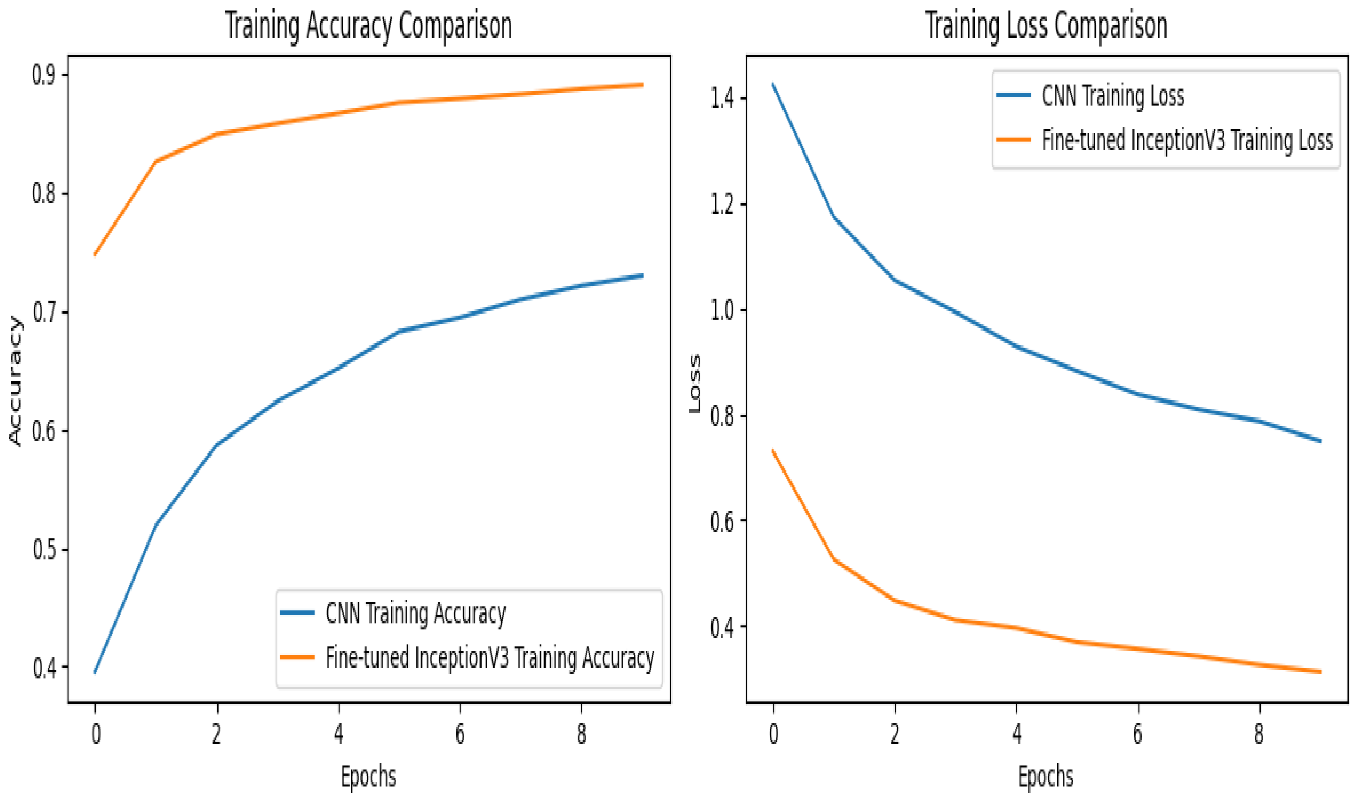
Model Compilation: Adam optimizer, sparse categorical cross entropy loss.

4

Training: 10 epochs with data augmentation, early stopping, and model checkpoint.

RESULTS COMPARISON

In comparing the models, the CNN trained from scratch exhibited an accuracy of 0.79. However, after fine-tuning InceptionV3, the model achieved a substantial improvement with an accuracy of 0.89. This highlights the efficacy of transfer learning in enhancing model performance for image classification tasks



LIMITATIONS AND AREAS OF IMPROVEMENT

Despite the success of transfer learning, there are inherent limitations and areas that warrant improvement. Challenges may arise in adapting pre-trained models to specific tasks, and there could be concerns about biases present in the initial training data. To address these limitations, continual evaluation, refinement of architectures, and exploration of diverse datasets are essential for the ongoing development and deployment of effective image classification models.