TRANSFER LEARNING FOR IMAGE CLASSIFICATION

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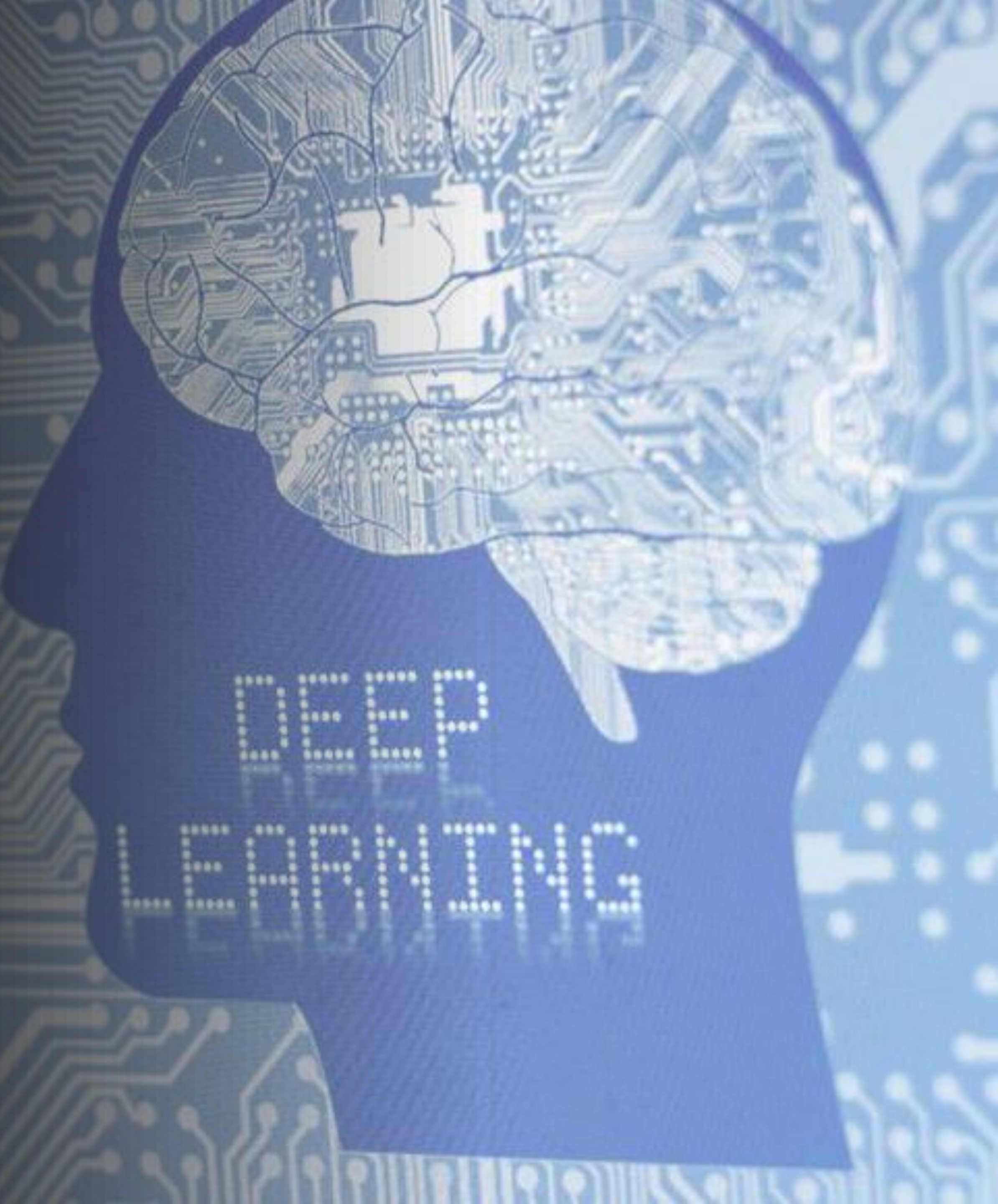


COLAB LINK: https://colab.research.google.com/drive/1QK0xY-RXsmtTdFgbc6RGlvJNvPNNwRlC?usp=sharing

CIFAR-10 DATASET

- CIFAR-10 stands for the Canadian Institute for Advanced Research - 10 classes.
  - Set of images which consists of 60,000 color images.
  - Split into 50000 training and 10000 testing.
  - Size 32*32 pixels.
  - Labelled in 10 distinct classes.

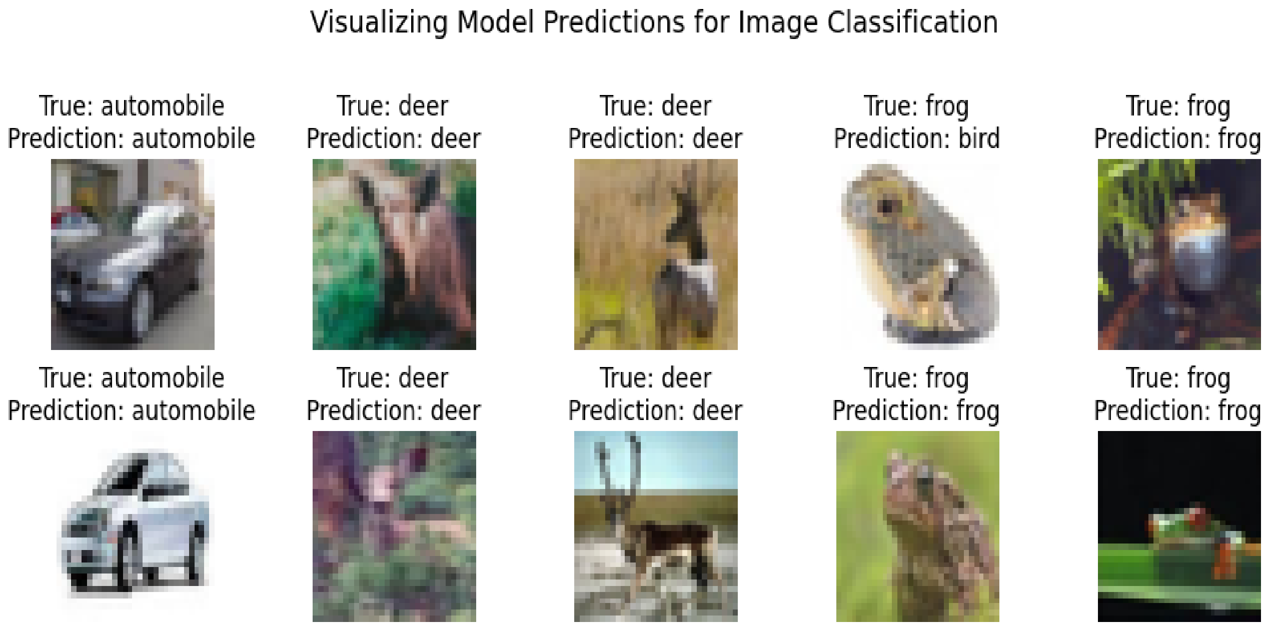
TRANSFER LEARNING

Traditional approach: Build every model from scratch?

- Time-consuming and expensive
- Challenges:
  - Extensive data collection and labelling are required
  - Privacy issues with large datasets
  - High training computational costs

Transfer learning: Key advantages

- Utilizes existing knowledge from pre-trained models
- Saves training time
- More practical
- Example: Image Classification



PRE-TRAINED MODEL - RESNET50

Deep neural network with 50 layers.

Proven expertise in precise image classification.

Trained on ImageNet for diverse feature extraction.

Transfer Learning Capability:

- Ideal for transfer learning tasks.
- Allows for efficient fine-tuning of specified datasets.

Advantages of ResNet50:

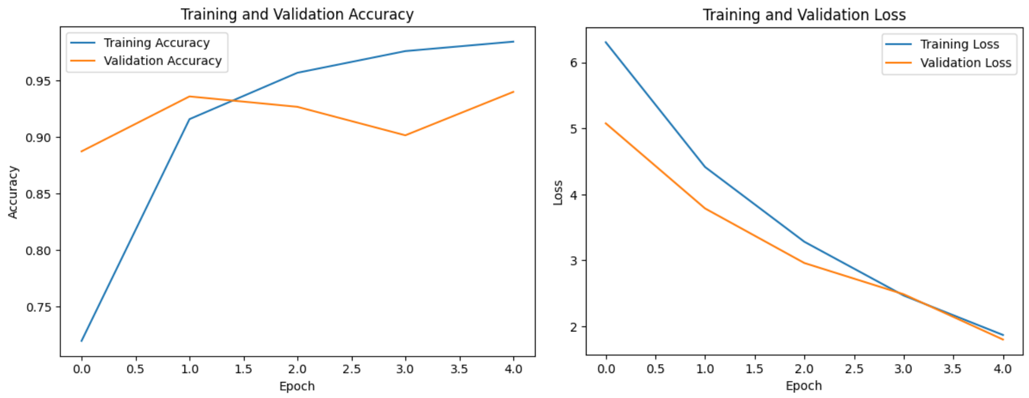
- Enables the model to learn hierarchical features effectively.
- Simplifies knowledge transfer with pre-trained weights.

FINE-TUNING IMPACT

- Utilized ImageNet for robust feature extraction.
- Up-sampled input images to (224 x 224) for ResNet compatibility.
- Layers initially frozen and gradually unfrozen for the last 90 layers. This strategic decision blends prior knowledge with adaptation to the CIFAR-10 dataset.
- Training Performance:
  - Conducted training over 5 epochs.
  - Early stopping implemented to reduce overfitting.
  - Tracked validation loss for effective model recovery.
- Regularization Techniques: Incorporated dropout layers to prevent overfitting.
- Compilation:
  - Used SGD as the optimizer.
  - Employed Sparse Categorical Crossentropy for a multi-class classification task.
- Achieved superior accuracy and efficiency through fine-tuning compared to training from scratch.

COMPARISION TRANSFER LEARNING (RESNET50) v/s SCRATCH

PRETRAINED MODEL



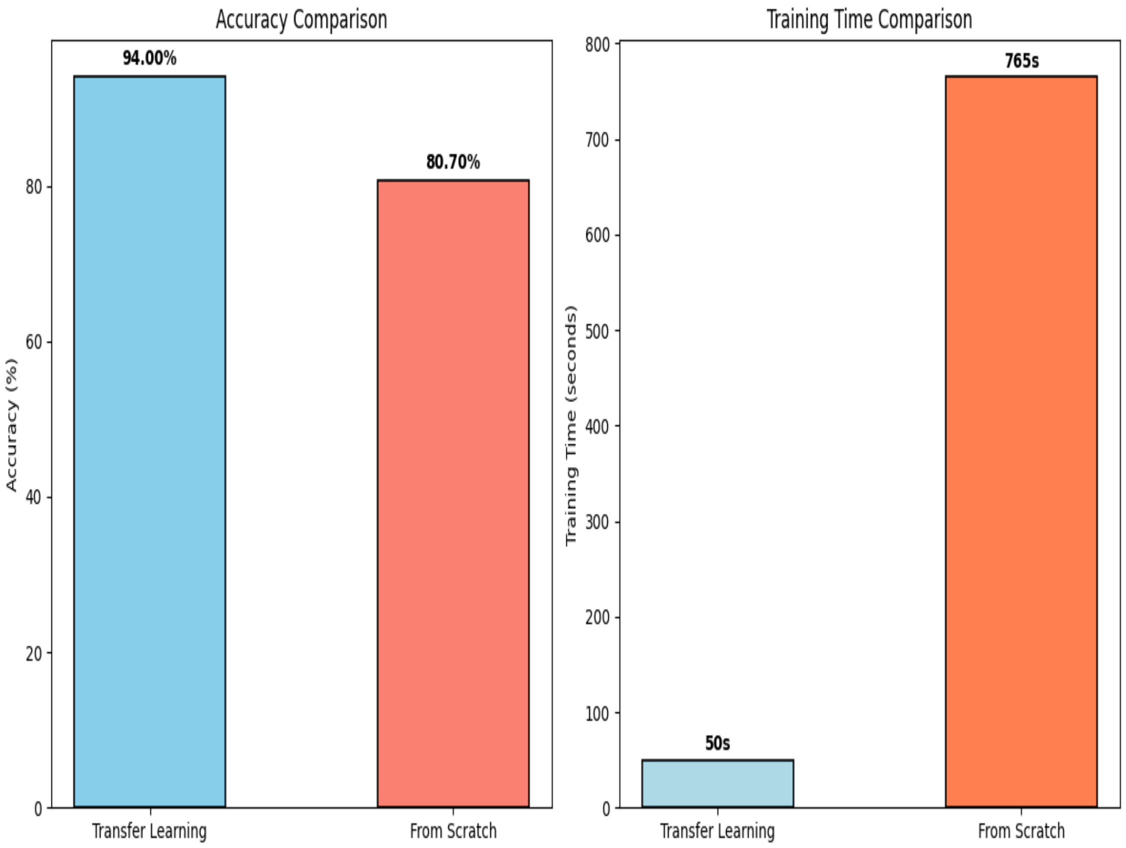
MODEL FROM SCRATCH

- High accuracy (94%) was achieved with only 5 training epochs, demonstrating the effectiveness of fine-tuning pre-trained models.
- Feature Extraction: Benefits from pre-trained features on ImageNet for enhanced pattern recognition.

- Simplicity: Uses a custom CNN architecture without pre-trained features.
- Training Requirements: Requires 18 epochs for 80.7% accuracy, demanding more training time.

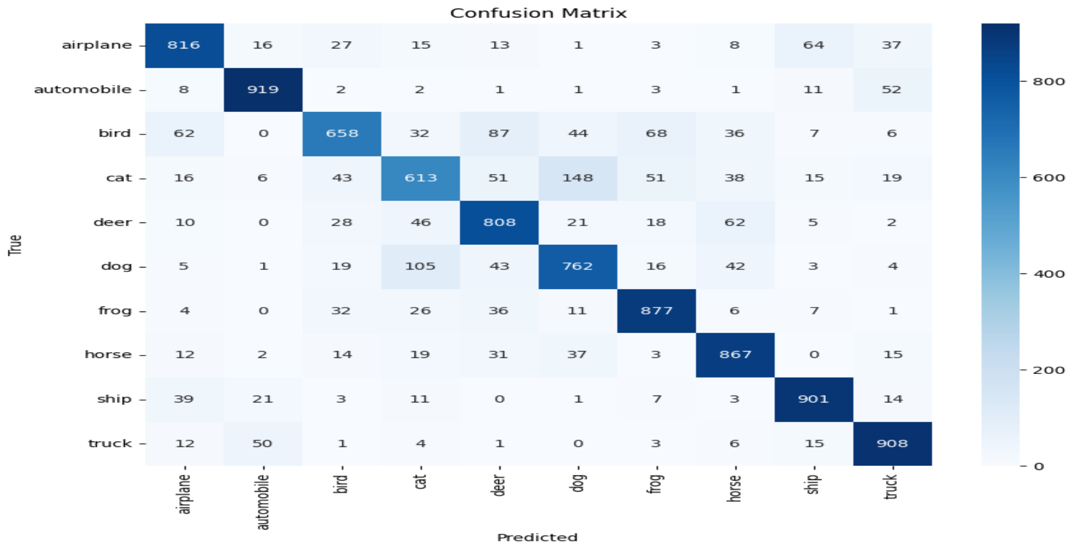
- ResNet excels, but it requires more resources. ResNet transfer learning provides improved performance by emphasizing resource considerations.

- The graph illustrates the changes in training time that come with using Transfer Learning and its accuracy advantage over training from scratch.
- Transfer Learning achieved remarkable outcomes, with a 94% accuracy rate and a training time of just 50 seconds.
- Even though From Scratch was 80.7% accurate, training took longer (765 seconds).
- Transfer Learning achieves high accuracy efficiently, whereas training from scratch requires more time for convergence.



- Resnet achieved a remarkable 94% overall accuracy in the classification report, demonstrating exceptional precision, recall, and F1-score across most classes.
- The CNN model achieved an overall accuracy of 81% and demonstrated commendable performance, but with lower metrics than ResNet.
- The confusion matrices for both ResNet and CNN show mostly accurate predictions across a wide range of classes, with some ambiguity in CNN's "aeroplane," "truck," and "cat" predictions.
- CNN has relatively lower confusion in comparison to ResNet.
- ResNet outperforms CNN in accuracy, precision, recall, and F1-score, demonstrating the benefit of transfer learning for robust image classification.

Fig 1: Confusion Matrix CNN Model



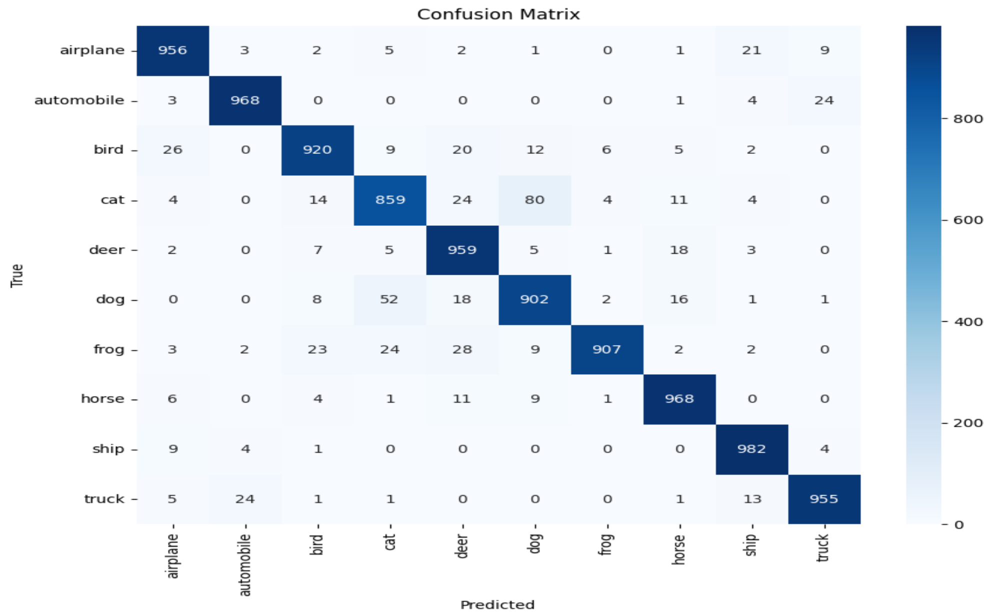


Fig 2: Confusion Matrix ResNet Model

LIMITATIONS AND POTENTIAL IMPROVEMENTS

Limitations:

- Small Dataset Size: CIFAR-10's small size may limit model exposure to a wide range of patterns.
- Class Imbalance: Uneven class distribution could lead to biassed model learning.
- Pre-training on ImageNet may not smoothly transfer knowledge to CIFAR-10.
- Fine-tuning and training from scratch demand substantial computational resources.

Potential Improvements:

- Data Augmentation: Implement advanced augmentation techniques to overcome challenges with tiny datasets.
- Examine pre-training on datasets with similar features and complexity to CIFAR-10.
- Optimize the model design and training method for parallel computing.

CONCLUSION

- Transfer Learning achieved exceptional accuracy (94%) on CIFAR-10, demonstrating its effectiveness.
- ResNet fine-tuning outperformed CNN in both accuracy and efficiency.
- The trade-off between accuracy and resource consumption was proven by training from scratch.
- Transfer Learning demonstrated resource efficiency by finishing training in 50 seconds.
- Hence transfer learning is ideal for applications that require precision while having limited computing time.
- In summary, the analysis provides significant insights that enable informed decisions in selecting models that balance accuracy and efficiency across varied applications.

REFERENCES

Bichri, H., Chergui, A. and Hain, M. (2023). Image Classification with Transfer Learning Using a Custom Dataset: Comparative Study. *Procedia Computer Science*, [online] 220, pp.48–54. doi:https://doi.org/10.1016/j.procs.2023.03.009.

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