Transfer Learning For Image Classification

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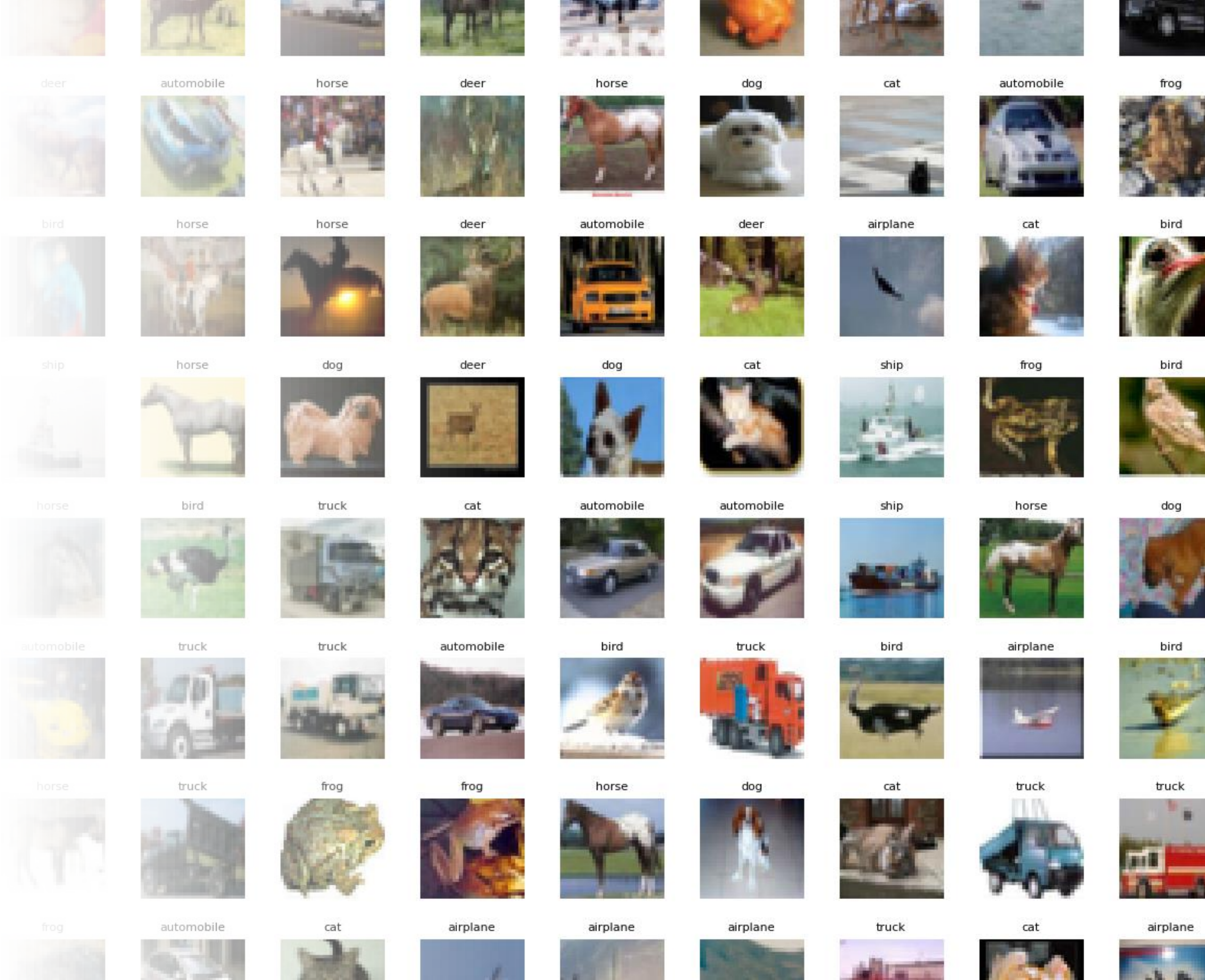
Colab Link:https://colab.research.google.com/drive/1_dIa-uNASRVl0kiXNbBqZ7MrV6KsEdoC?usp=sharing

CIFAR-10

- **CIFAR-10 comprises 60,000 32x32 color images.**
- **Images are distributed across 10 diverse classes.**
- **All images are compact, with a size of 32x32 pixels.**
- **Classes include airplanes, automobiles, birds, cats, among others.**
- **Widely used for object recognition tasks in machine learning.**



Transfer Learning

- Adapting a model learned on one task for a similar task is known as transfer learning.
- Applies knowledge obtained from one problem to increase performance in another.
- Increases the speed of training convergence.
- Useful in situations with a limited amount of labeled data.
- Utilizes findings from pre-trained models.
- Particularly advantageous for tasks like image classification.
- Makes it possible to apply learned characteristics to different datasets.

Pre-training model :

ResNet50

•Chosen for its remarkable depth and outstanding performance.

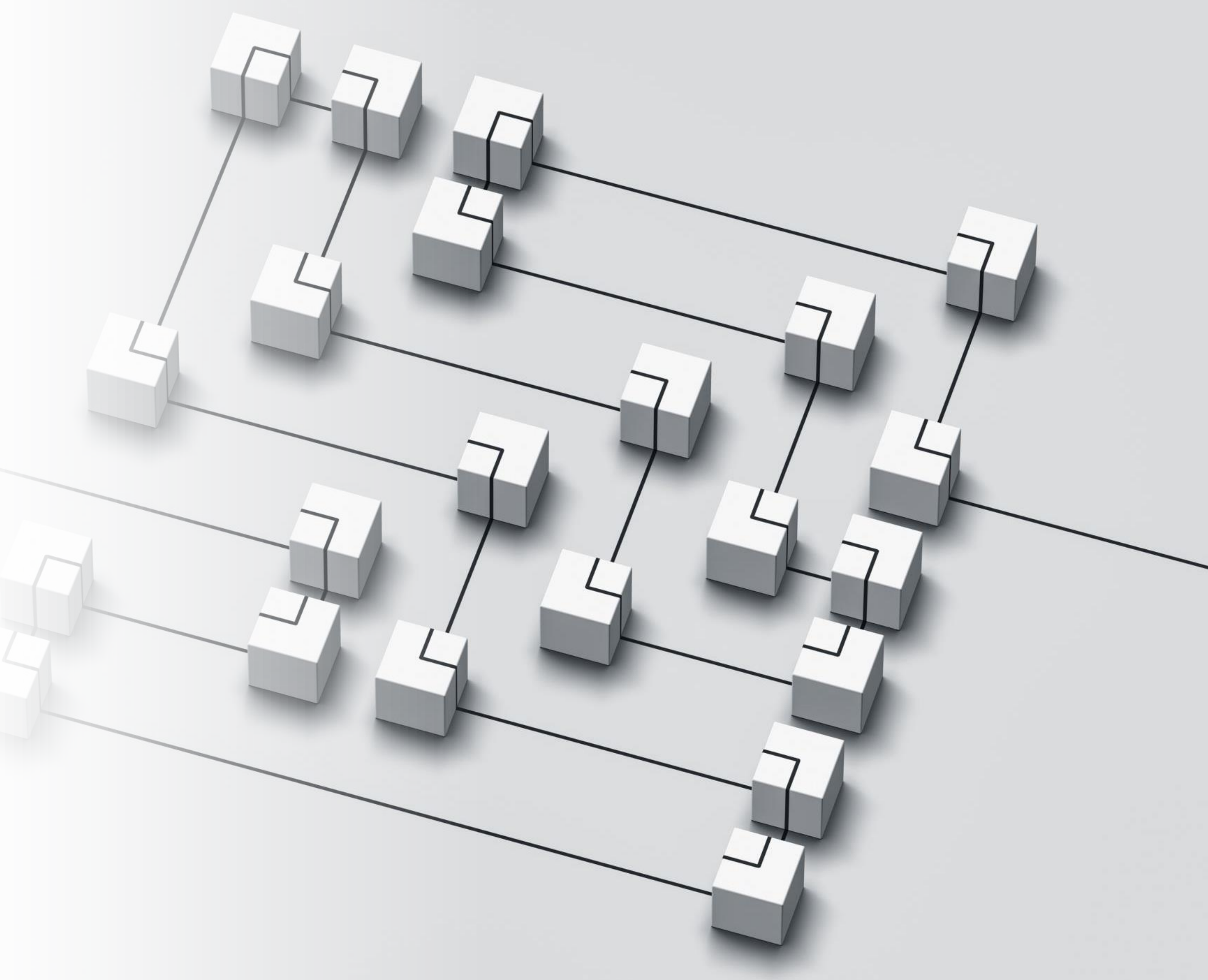
•Showcased excellence in large-scale image classification through previous training on ImageNet.

•Selected for transfer learning on CIFAR-10 due to its depth and well-established feature extraction capabilities.

•ResNet50's depth facilitates capturing detailed features, making it ideal for nuanced image classification.

•The application of residual learning ensures a seamless adaptation during transfer tasks.

•Serves as the fundamental architecture for fine-tuning in Keras on CIFAR-10.

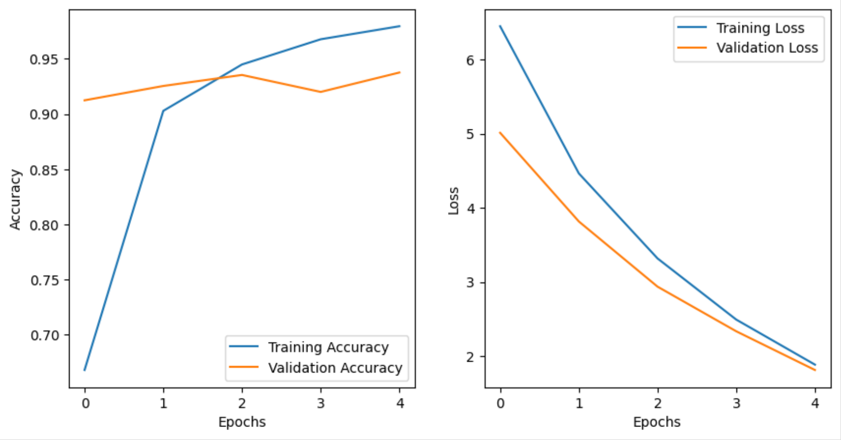


Fine-tuning

- Fine-tuning involves tailoring the pre-trained ResNet50 to our specific image classification task on CIFAR-10.
- Initial layers are frozen to retain general features.
- Subsequent layers are unfrozen to capture task-specific nuances.
- Frozen layers maintain general image understanding, while unfrozen layers capture task-specific intricacies.
- Learning rates and optimizers are tuned for optimal performance during fine-tuning.
- Increased dropout rates are applied to prevent overfitting.
- The fine-tuning process customizes ResNet50 for CIFAR-10, maximizing its effectiveness in our image classification endeavor.

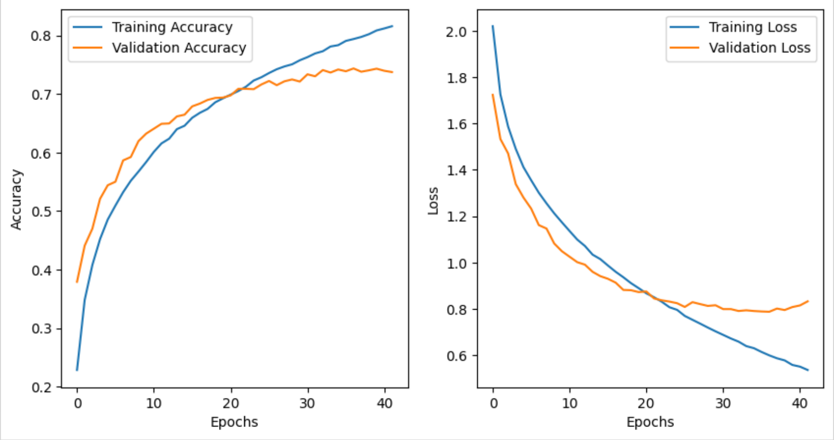
Pre-trained Model

- Achieved an impressive 93.79% test accuracy.
- Quick convergence in just 5 epochs.
- Leveraged pre-trained features for nuanced image classification.
- Fine-tuned the last 100 layers for optimal adaptation.



Scratch Model

- Attained a respectable 72.37% test accuracy.
- Required a more extended training period, reaching peak accuracy in 42 epochs.
- Simpler architecture highlighted the potential of starting from scratch.
- Faced challenges in capturing intricate features compared to ResNet50.



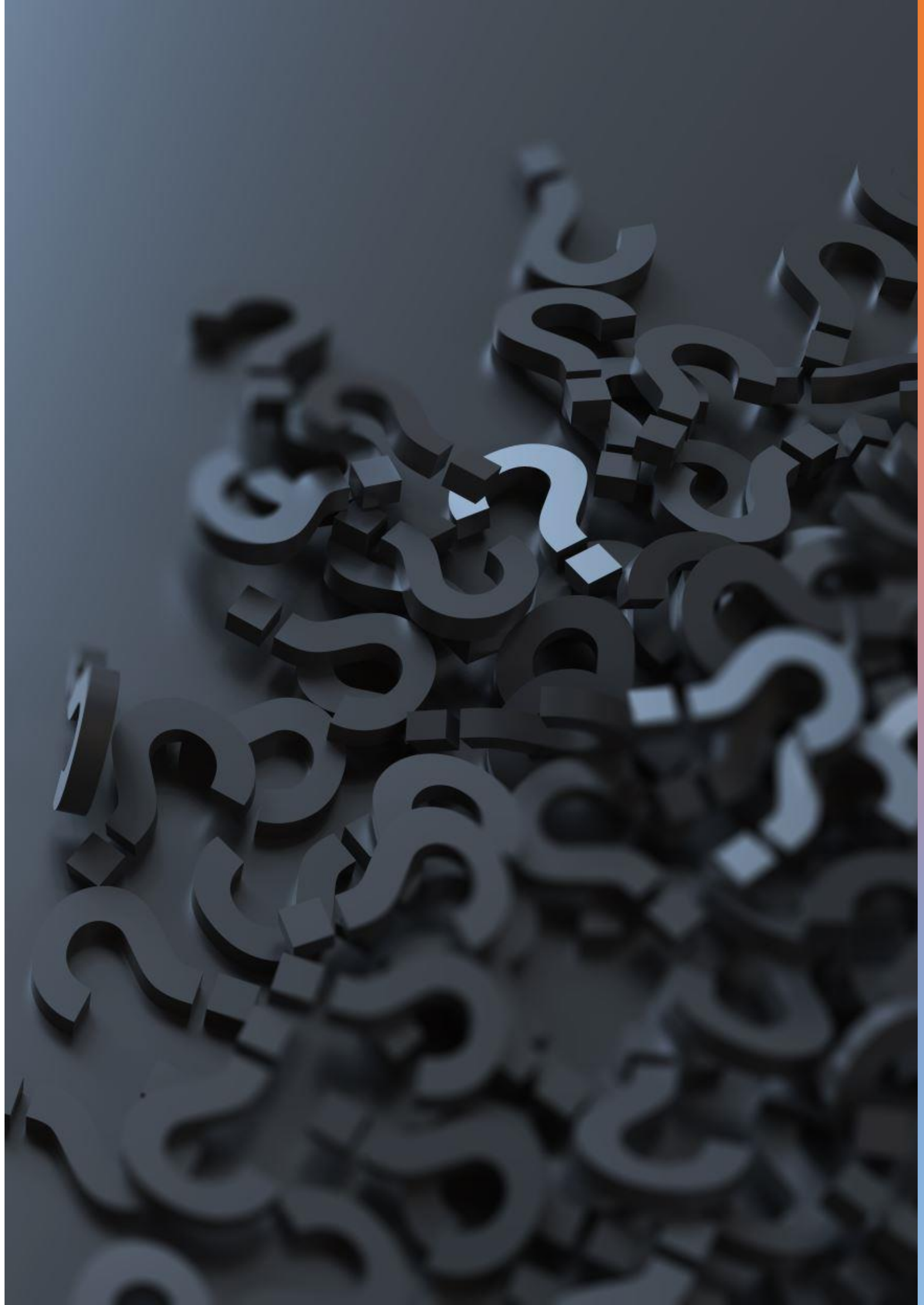
ResNet50 excelled in accuracy and efficiency, thanks to its depth and pre-trained features.The CNN model showcased the potential of simplicity and building models from the ground up.

Limitations:

- ResNet50's computational requirements limit its widespread use.
- Success in transfer learning relies on dataset similarity, which presents challenges for a variety of applications.
- Pre-trained models could include biases that affect how fair predictions are.
- Determining optimal layers for fine-tuning adds complexity.

Efficiency Enhancements:

- For wider accessibility, look into lighter models or distillation methods.
- Customize strategies for diverse datasets to enhance adaptability.
- Use strategies to identify and correct biases so that predictions are fair.
- Develop automated methods for efficient layer selection and fine-tuning.



Ethical Reflections

Identify potential biases in pre-trained models that are used to classify images and take appropriate action.

Emphasize the significance of utilizing AI sensibly while taking society's potential effects into account.

Promote transparent and intelligible decision-making procedures to foster accountability and confidence.

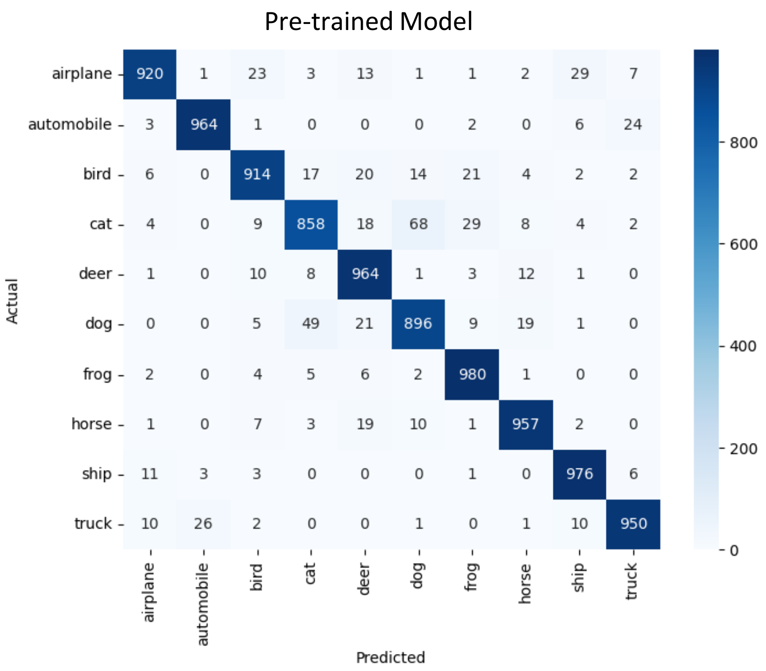
Reduce biases in picture categorization by employing techniques like building different datasets.

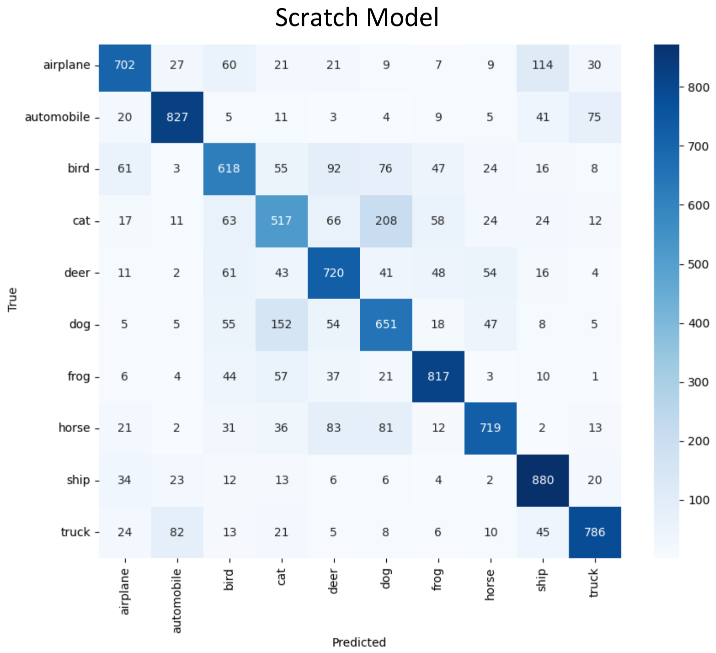
Involve the public in order to resolve issues and guarantee ethical use of AI.

Conclusion

- Our CIFAR-10 transfer learning, anchored by ResNet50, illustrates the efficiency improvements of using pre-trained models. This simplifies intricate designs and highlights the usefulness of effective model creation.

- Pre-trained models' biases are acknowledged by ethical considerations. Challenges like computing intensity are tackled with strategic solutions, such as investigating lighter models and automated fine-tuning, affecting the progress of transfer learning.





Reference

Dabydeen, A. (2019). *Transfer Learning Using ResNet50 and CIFAR-10*. [online] Medium. Available at: https://medium.com/@andrew.dabydeen/transfer-learning-using-resnet50-and-cifar-10-6242ed4b4245 [Accessed 16 Jan. 2024].

Ruiz, P. (2018). *ResNets for CIFAR-10*. [online] Medium. Available at: https://towardsdatascience.com/resnets-for-cifar-10-e63e900524e0.