Image Classification

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Exploring the Dataset

CIFAR-10:

- This Dataset has 10 distinct classes representing various objects and animals.
- Each image has a diverse collection comprising 60,000 32x32 color images.

Class Labels:

- Categories of the Images in the dataset are Airplane, Automobile, Bird, Cat, Deer, Dog, Frog, Horse, Ship, Truck.

Significance and Challenges:

- This dataset is widely used in machine learning for evaluating image classification algorithms and this dataset is a benchmark dataset for image classification

- Small-sized images pose challenges and encourage robust model design.

Reasons for Choosing CIFAR-10:

Real-world Relevance: The dataset represents common everyday objects, making it applicable to real-world image classification scenarios.

Diversity: The dataset covers a diverse range of object categories, challenging the model to generalize across different types of images.

Size: CIFAR-10's moderate size strikes a balance between feasibility for experimentation and providing sufficient complexity for meaningful model evaluation.

Visual Representation:
Below Images are the example class images of the Dataset

Understanding Transfer Learning:

Transfer learning is a machine learning technique where a model developed for one task is leveraged as a starting point for a model on a different task.

Importance:

Knowledge Transfer: Allows the reuse of knowledge learned from one domain to improve performance on a related task.

Data Efficiency: Significantly reduces the need for large labelled datasets, particularly beneficial in scenarios with limited labelled data.

Faster Training: Accelerates model training by initializing with pre-learned weights, particularly advantageous for deep neural networks.

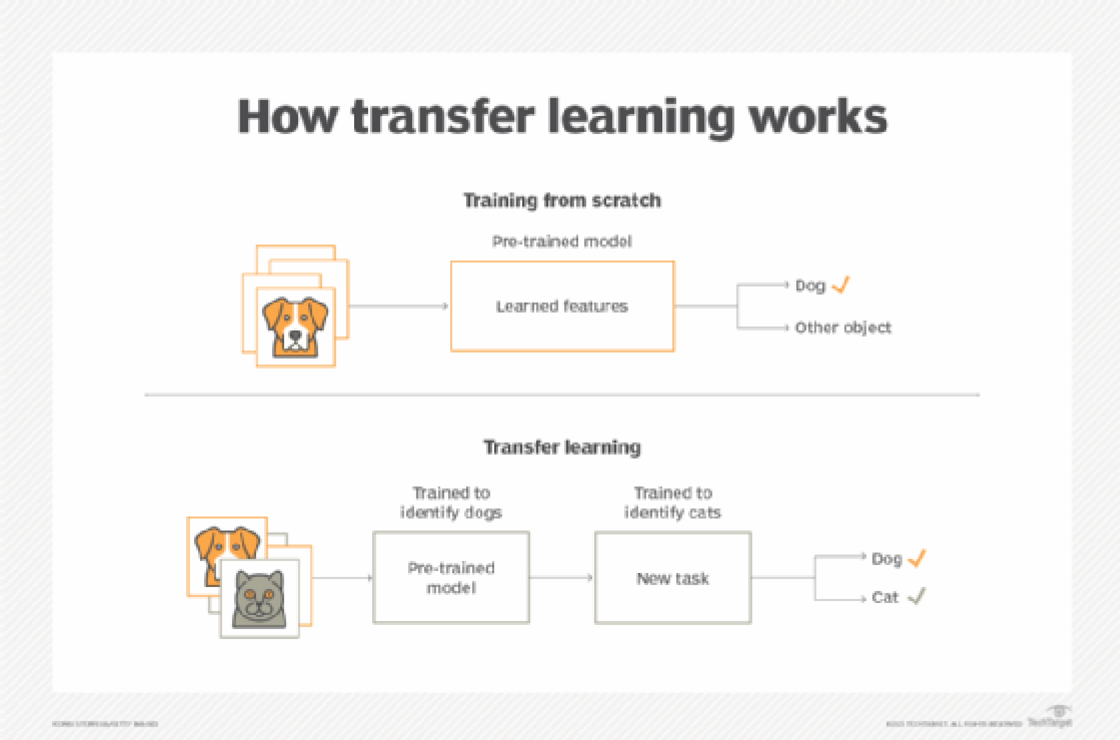
Generalization: Enhances the model's ability to generalize across tasks, leading to better performance on new, unseen data.

Applications:

- **Image Classification:** Particularly effective in image classification tasks, where features learned from one dataset can be beneficial for a different but related dataset.
- **Natural Language Processing:** Applied in tasks such as sentiment analysis, text classification, and language translation

Considerations:

- **Domain Similarity:** The effectiveness of transfer learning depends on the similarity between the source and target domains.
- **Layer Selection:** Choosing which layers to freeze or fine-tune is crucial for optimal transfer learning performance.



Choosing a Pre-trained Model

After experimenting with various pre- trained models like **MobileNet, ResNet50** and **VGG16**. VGG16 is selected for its balanced performance and capacity.

With the Pre trained model **MobileNet** without freezing the layers, A accuracy of **22%** is achieved. And after Experimenting and freezing different sets of layers, accuracy of **83.27%** is achieved with freezing top 8 layers

With the Model **ResNet50**, Without freezing any layers it has a accuracy of 40%, And with freezing bottom 12 layers, a accuracy of 83.12% is achieved.

And finally, the **VGG16** layer is chosen as it is giving a high accuracy varying between 86-90% and it is achieved by freezing last 12 layers

And along with the VGG16, tried data Augementation but failed in getting better accuracy.

VGG16 Model:

VGG16 Model consists of 16 layers, including 13 convolutional layers and 3 fully connected layers.

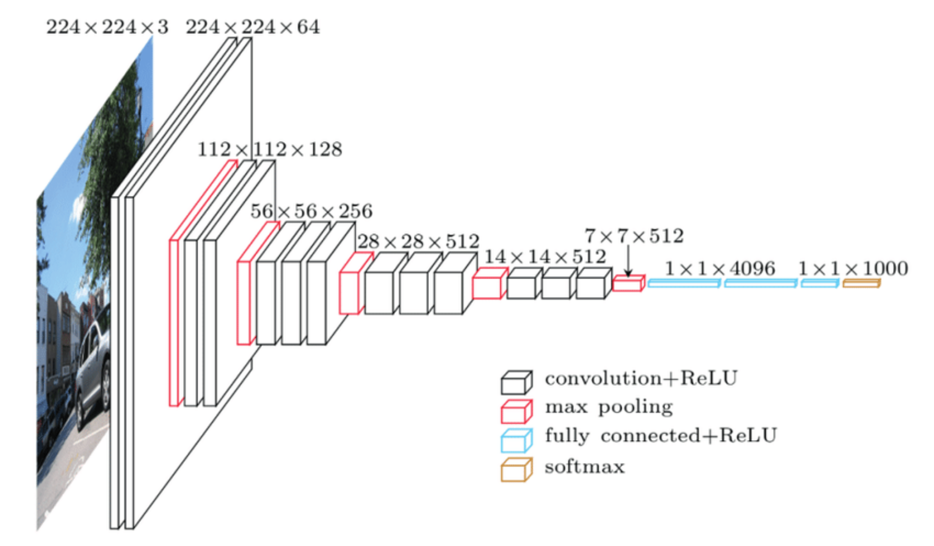
In the Process of experimenting the model, so many things were learned.

Especially, the Fine tuning process. As freezing the layers increased the accuracy of the model, As the layers which are unfrozen gets the chance to learn.

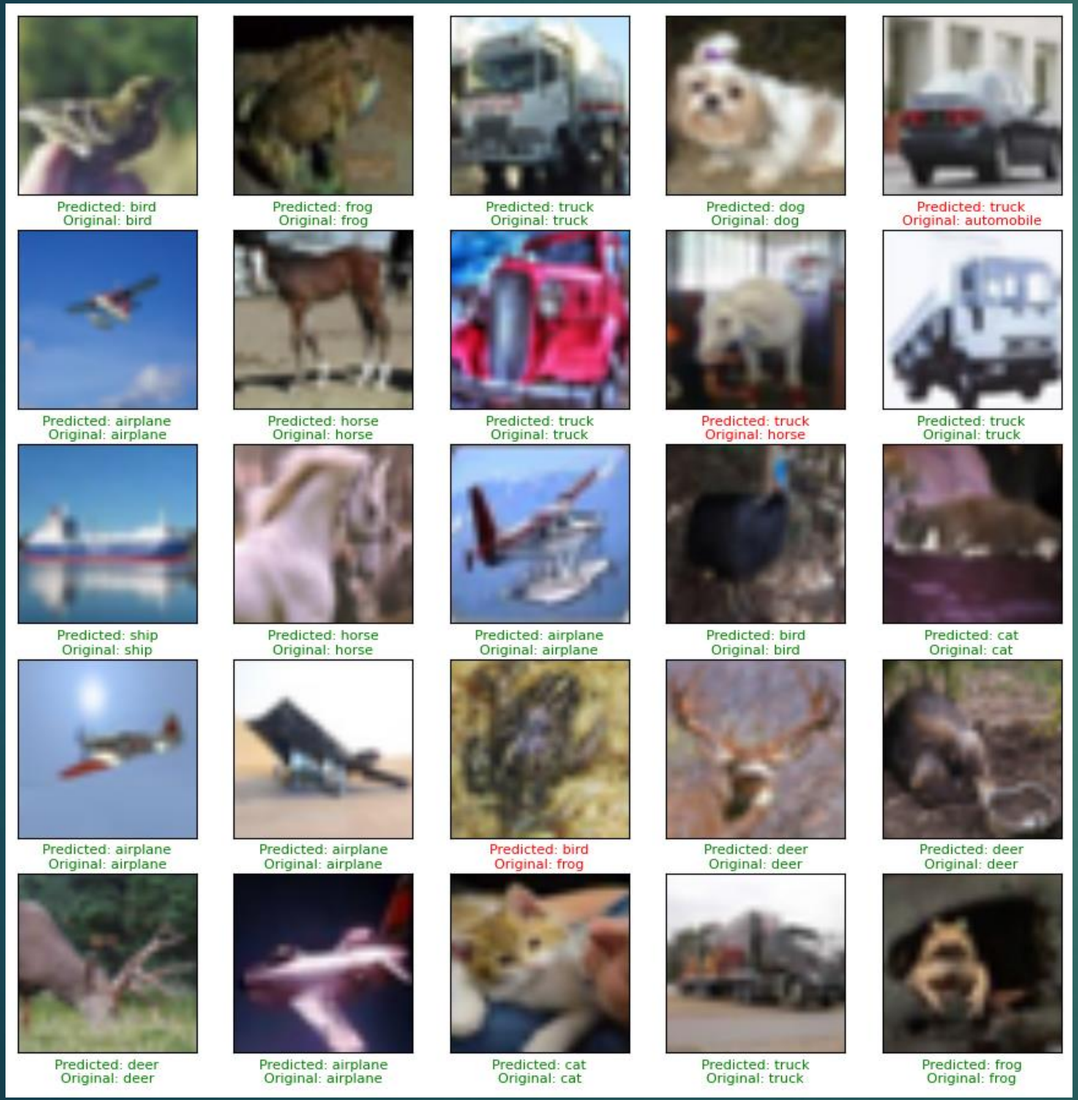
Steps followed along with the accuracy of the model in the model

- Freezing all the layers – 60 %
- Freezing all the layers except last 5 -73%
- Change of learning rate from 0.0001 to 0.00005 – 76%
- Freezing all except last 12 with 0.0005 gives accuracy of 87%

used early stopping and used 50 epoches and it got stopped at 36 epochs and got 87% accuracy

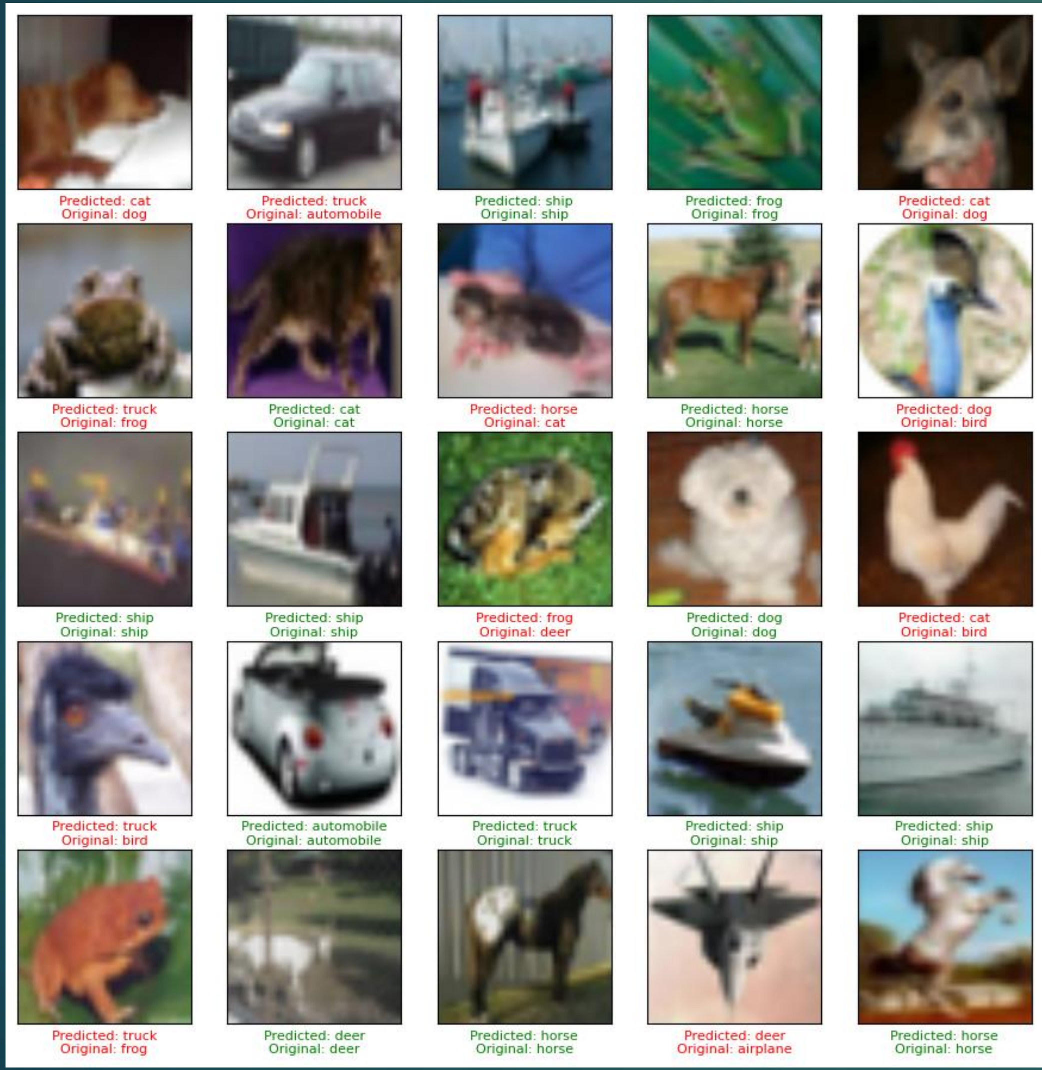


Result Obtained from Transfer Learning



- The results were generated through training a pretrained model
- And the trained model is predicted with the 20% test data and results were shown.
- Below the image the original values and predicted results were shown, Incorrect predictions are visually highlighted in red. And the Correct predictions are visually marked in green.
- So, With the total of 25 images, 3 images were predicted wrongly
- In the 5^{th} Image automobile is classified as Truck, so that mean The characteristics of automobile is coinciding with that of truck

Result Obtained from Model scratch



- These results are generated from model which is trained from scratch.
- As this model is not trained from any other model, it will not have any knowledge of images,
- The model incorporates convolutional and pooling layers and have obtained accuracy of 76% in predictions
- And of out 25 images, 10 images were incorrectly predicted with this standalone model, This highlights the inherent challenges and limitations of training a model from scratch, particularly in scenarios where diverse and complex features are crucial for accurate classification.
- And for all the outputs, used interpolation for generating better images

Conclusion:

- Upon comparing, It is a clear winner that the transfer learning outperformed the model which is build from scratch. As we integrated knowledge from pre-trained layers, the transfer learning model showcased swift convergence and attained exceptional accuracy.

- Contrarily, Scratch model initiated with no prior knowledge faced hurdles. The lack of pre-existing insights resulted in prolonged training durations, delayed convergence and less accurate. These models encountered difficulties in grasping nuanced patterns and features within the dataset, impeding their overall efficacy.

- In summary, transfer learning stands out as the recommended method for CIFAR-10 classification and comparable assignments. Its adept utilization of pre-existing knowledge accelerates convergence and augments accuracy, presenting a distinct edge over the conventional approach of starting from scratch