MLP

* Application: Tabular/structured data (e.g., medical records, financial data).
* Architecture: Fully connected layers with activation functions like ReLU and sigmoid.

* Works well on structured datasets.
* Easy to implement and train.

* Cannot effectively capture spatial relationships (e.g., in image data).
* Requires careful feature scaling and encoding.

CNN

* Application: Image and spatial data (e.g., object detection, handwriting recognition).
* Architecture: Uses convolutional and pooling layers to learn spatial hierarchies.

* Automatically extracts spatial features (edges, textures, shapes).
* Outperforms MLPs on image tasks.

* Requires more data and compute than MLPs.
* Not suitable for non-spatial/tabular data.

Effects of transfer learning:

Using a CNN pretrained on a large dataset (e.g., ImageNet) and adapting it to a new task.

How it works:

* Reuse early layers that capture general features.
* Fine-tune later layers on your custom dataset.

Transfer learning significantly improves accuracy on small datasets, reduces training time and the risk of overfitting, and requires less labeled data.