

```
In [14]: import tensorflow as tf
from tensorflow.keras import layers, models
from tensorflow.keras.applications import MobileNetV2
from tensorflow.keras.callbacks import EarlyStopping, Callback
import psutil
import time
import GPUUtil
import matplotlib.pyplot as plt
```

```
In [3]: img_size = (224, 224)
batch_size = 32

train_ds = tf.keras.utils.image_dataset_from_directory(
    "../dataset/training_set",
    image_size=img_size,
    batch_size=batch_size
)

val_ds = tf.keras.utils.image_dataset_from_directory(
    "../dataset/test_set",
    image_size=img_size,
    batch_size=batch_size
)
```

Found 8000 files belonging to 2 classes.

Found 2000 files belonging to 2 classes.

```
In [4]: AUTOTUNE = tf.data.AUTOTUNE

train_ds = train_ds.prefetch(buffer_size=AUTOTUNE)
val_ds = val_ds.prefetch(buffer_size=AUTOTUNE)
```

```
In [5]: def get_cpu_ram():
    cpu_percent = psutil.cpu_percent(interval=1)
    ram = psutil.virtual_memory()
    ram_used_mb = ram.used / (1024 ** 2)
    return cpu_percent, ram_used_mb

def get_gpu_stats():

    try:
        gpus = GPUUtil.getGPUs()
        if not gpus:
            return None, None, None
        gpu = gpus[0]
        return gpu.load * 100, gpu.memoryUsed, gpu.memoryTotal
    except:
        return None, None, None
```

```
In [6]: cpu_before, ram_before = get_cpu_ram()
gpu_before, vram_used_before, vram_total_before = get_gpu_stats()

msg = f"AVANT entraînement -> CPU: {cpu_before:.1f}% | RAM: {ram_before:.0f} MB"
if gpu_before is not None:
    msg += f" | GPU: {gpu_before:.1f}% | VRAM: {vram_used_before}/{vram_total_be
print(msg)
```

AVANT entraînement → CPU: 7.4% | RAM: 5724 MB | GPU: 0.0% | VRAM: 0.0/4096.0 MB

```
In [7]: base_model = MobileNetV2(  
    input_shape=(224, 224, 3),  
    include_top=False,  
    weights="imagenet"  
)  
  
base_model.trainable = False
```

```
In [8]: model = models.Sequential([  
    base_model,  
    layers.GlobalAveragePooling2D(),  
    layers.Dense(128, activation="relu"),  
    layers.Dropout(0.3),  
    layers.Dense(1, activation="sigmoid")  
])
```

```
In [9]: model.compile(  
    optimizer="adam",  
    loss="binary_crossentropy",  
    metrics=["accuracy"]  
)
```

```
In [10]: early_stop = EarlyStopping(  
    monitor="val_loss",  
    patience=5,  
    restore_best_weights=True  
)  
  
class PerformanceCallback(Callback):  
    def on_epoch_begin(self, epoch, logs=None):  
        self.start_time = time.time()  
  
    def on_epoch_end(self, epoch, logs=None):  
        cpu, ram = get_cpu_ram()  
        gpu, vram_used, vram_total = get_gpu_stats()  
        duration = time.time() - self.start_time  
  
        msg = f" | CPU: {cpu:.1f}% | RAM: {ram:.0f} MB | Time: {duration:.1f}s"  
        if gpu is not None:  
            msg += f" | GPU: {gpu:.1f}% | VRAM: {vram_used}/{vram_total} MB"  
        print(msg)
```

```
In [11]: history = model.fit(  
    train_ds,  
    validation_data=val_ds,  
    epochs=10,  
    callbacks=[early_stop, PerformanceCallback()]  
)
```

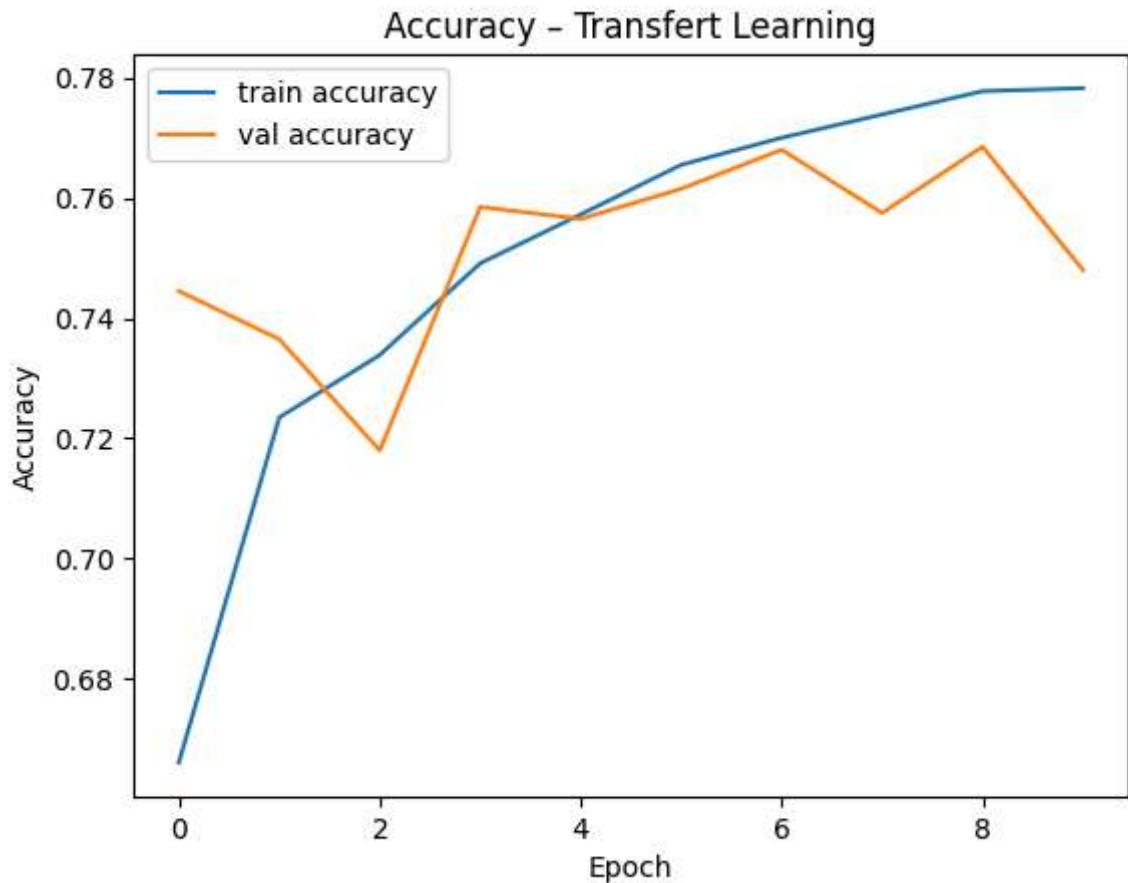
Epoch 1/10  
250/250 [=====] - ETA: 0s - loss: 0.6161 - accuracy: 0.661 | CPU: 1.8% | RAM: 5834 MB | Time: 181.0s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 181s 712ms/step - loss: 0.6161 - accuracy: 0.6661 - val\_loss: 0.5407 - val\_accuracy: 0.7445  
Epoch 2/10  
250/250 [=====] - ETA: 0s - loss: 0.5464 - accuracy: 0.7235 | CPU: 4.5% | RAM: 5833 MB | Time: 157.3s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 157s 629ms/step - loss: 0.5464 - accuracy: 0.7235 - val\_loss: 0.5292 - val\_accuracy: 0.7365  
Epoch 3/10  
250/250 [=====] - ETA: 0s - loss: 0.5264 - accuracy: 0.7339 | CPU: 1.8% | RAM: 5646 MB | Time: 158.1s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 158s 632ms/step - loss: 0.5264 - accuracy: 0.7339 - val\_loss: 0.5385 - val\_accuracy: 0.7180  
Epoch 4/10  
250/250 [=====] - ETA: 0s - loss: 0.5025 - accuracy: 0.7491 | CPU: 2.1% | RAM: 5380 MB | Time: 156.4s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 156s 626ms/step - loss: 0.5025 - accuracy: 0.7491 - val\_loss: 0.5042 - val\_accuracy: 0.7585  
Epoch 5/10  
250/250 [=====] - ETA: 0s - loss: 0.4913 - accuracy: 0.7573 | CPU: 0.6% | RAM: 5390 MB | Time: 155.6s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 156s 623ms/step - loss: 0.4913 - accuracy: 0.7573 - val\_loss: 0.4962 - val\_accuracy: 0.7565  
Epoch 6/10  
250/250 [=====] - ETA: 0s - loss: 0.4817 - accuracy: 0.7655 | CPU: 0.0% | RAM: 5411 MB | Time: 156.5s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 157s 626ms/step - loss: 0.4817 - accuracy: 0.7655 - val\_loss: 0.4918 - val\_accuracy: 0.7615  
Epoch 7/10  
250/250 [=====] - ETA: 0s - loss: 0.4723 - accuracy: 0.7700 | CPU: 0.6% | RAM: 5598 MB | Time: 161.1s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 161s 645ms/step - loss: 0.4723 - accuracy: 0.7700 - val\_loss: 0.4880 - val\_accuracy: 0.7680  
Epoch 8/10  
250/250 [=====] - ETA: 0s - loss: 0.4669 - accuracy: 0.7739 | CPU: 1.0% | RAM: 5614 MB | Time: 157.6s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 158s 631ms/step - loss: 0.4669 - accuracy: 0.7739 - val\_loss: 0.4931 - val\_accuracy: 0.7575  
Epoch 9/10  
250/250 [=====] - ETA: 0s - loss: 0.4590 - accuracy: 0.7778 | CPU: 2.2% | RAM: 5608 MB | Time: 158.2s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 158s 633ms/step - loss: 0.4590 - accuracy: 0.7778 - val\_loss: 0.4884 - val\_accuracy: 0.7685  
Epoch 10/10  
250/250 [=====] - ETA: 0s - loss: 0.4552 - accuracy: 0.7782 | CPU: 2.1% | RAM: 5494 MB | Time: 157.6s | GPU: 1.0% | VRAM: 0.0/4096.0 MB  
250/250 [=====] - 158s 631ms/step - loss: 0.4552 - accuracy: 0.7782 - val\_loss: 0.5096 - val\_accuracy: 0.7480

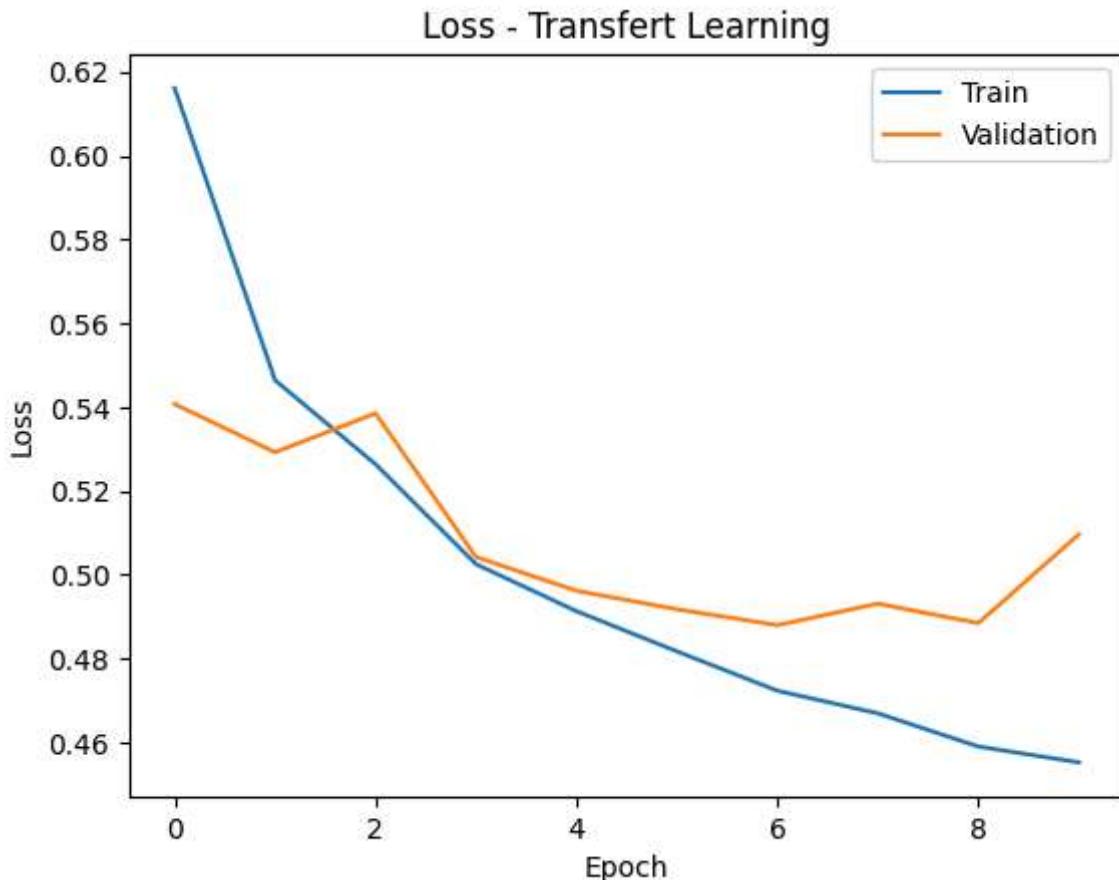
```
In [12]: cpu_after, ram_after = get_cpu_ram()
gpu_after, vram_used_after, vram_total_after = get_gpu_stats()

msg = f"APRÈS entraînement -> CPU: {cpu_after:.1f}% | RAM: {ram_after:.0f} MB"
if gpu_after is not None:
    msg += f" | GPU: {gpu_after:.1f}% | VRAM: {vram_used_after}/{vram_total_after}"
print(msg)
```

APRÈS entraînement -> CPU: 4.6% | RAM: 5551 MB | GPU: 1.0% | VRAM: 0.0/4096.0 MB

```
In [16]: plt.figure()
plt.plot(history.history["accuracy"], label="train accuracy")
plt.plot(history.history["val_accuracy"], label="val accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
plt.title("Accuracy - Transfert Learning")
plt.show()
plt.plot(history.history["loss"])
plt.plot(history.history["val_loss"])
plt.xlabel("Epoch")
plt.ylabel("Loss")
plt.legend(["Train", "Validation"])
plt.title("Loss - Transfert Learning")
plt.show()
```





## Conclusion

Les courbes de loss et d'accuracy montrent une convergence rapide du modèle, avec une amélioration nette des performances dès les premières epochs. La loss de validation diminue de manière régulière et l'accuracy atteint rapidement un niveau élevé, tandis que l'écart entre entraînement et validation reste limité, indiquant une bonne généralisation et l'absence de surapprentissage significatif.

Le suivi du temps d'entraînement par epoch met en évidence un coût computationnel important lié à l'exécution sur CPU, mais stable tout au long de l'apprentissage. La matrice de confusion confirme que la majorité des images sont correctement classées, avec quelques erreurs résiduelles liées à des images ambiguës. Ces résultats montrent que le transfert learning est particulièrement adapté au problème Dogs & Cats, permettant d'obtenir de très bonnes performances avec un effort d'entraînement limité.

In [ ]: