

WEEK-14

Aim :- TO Implement a pre-trained CNN model as a feature Extractor using transfer learning models.

objective :-

- TO understand transfer learning and feature extraction.
- TO reuse features learned from Imagenet for a new task.
- TO reduce training time and improve accuracy.
- Replace and train the final classification layer on a new dataset.

Algorithm :-

- 1) Load the dataset (eg:- cats vs dogs)
- 2) Load pre-trained model.
- 3) Freeze convolutional base layers.
- 4) Add new custom dense layers for classification.
- 5) compile and train on small dataset.
- 6) Evaluate accuracy.

pseudocode :-

Load VGG16 (weights='Imagenet', include_top=False)

Freeze all layers

Add Flatten() → Dense(128,relu) →
Dense(num_classes,softmax)

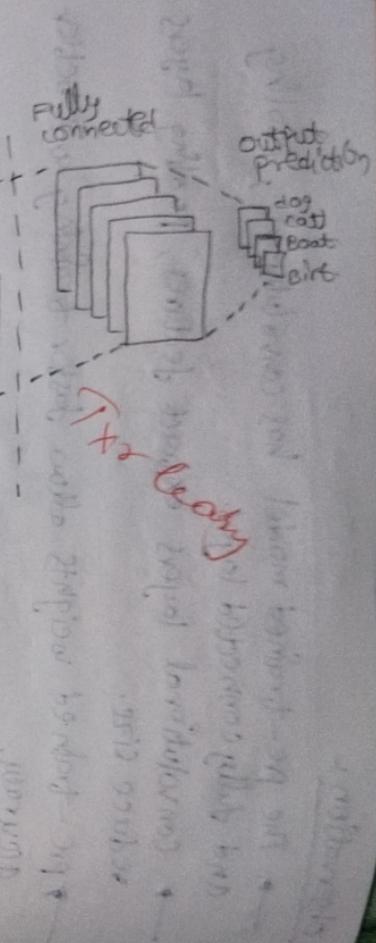
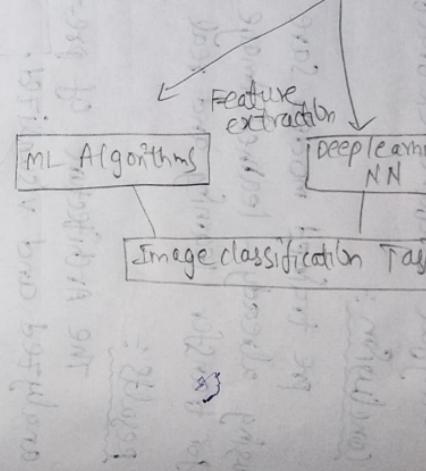
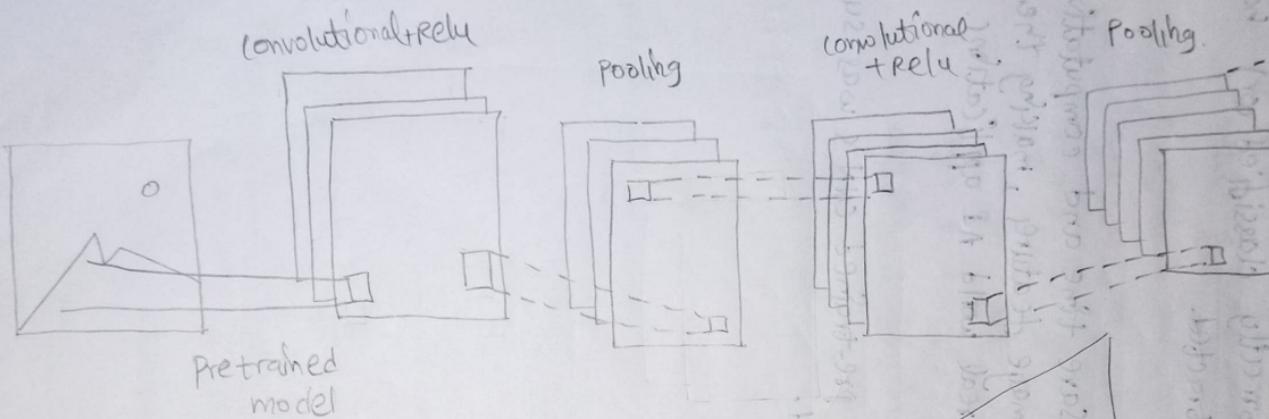
model = pretraihned-base + new-~~head~~ head.

compile(optimizer='adam', loss='categorical_crossentropy')

train on new dataset

Evaluate performance.

TRANSFER LEARNING



Output:

Epoch [1/5], Loss: 0.8481

Epoch [2/5], Loss: 0.6266

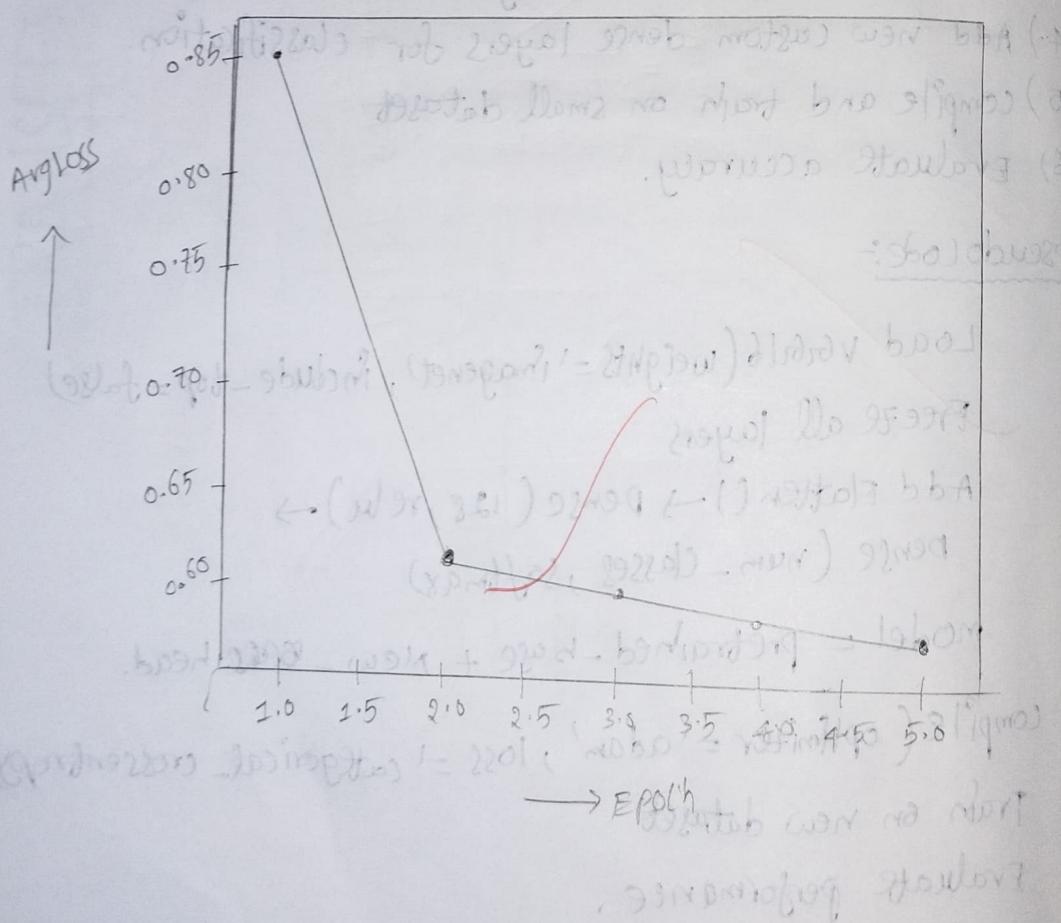
Epoch [3/5], Loss: 0.5937

Epoch [4/5], Loss: 0.5797

Epoch [5/5], Loss: 0.5699

Training complete using pre-trained ResNet 18 as feature extraction.

Training Loss curve—Transfer Learning with ResNet 18.



Observation :-

- Their pre-trained ResNet 18 achieved good accuracy even with few epochs.
- Training loss decreased steadily, confirming effective feature use.
- Test accuracy remained stable, showing generalization from pre-learned features.
- Model performed well even with small dataset.

Conclusion :-

Transfer learning allows reuse of learned visual features from large datasets, improving model accuracy and reducing training cost for new applications.

Result :-

The pre-trained CNN successfully extracted useful features and provided high classification accuracy on a new dataset.

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```
import tensorflow as tf
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.cifar10.load_data()

x_train, y_train = x_train[:10000], y_train[:10000]
x_test, y_test = x_test[:2000], y_test[:2000]
x_train = x_train.astype("float32") / 255.0
x_test = x_test.astype("float32") / 255.0

base_model = tf.keras.applications.MobileNetV2(
    input_shape=(64, 64, 3),
    include_top=False,
    weights='imagenet'
)
base_model.trainable = False # freeze layers
model = tf.keras.Sequential([
    layers.Resizing(64, 64),
    base_model,
    layers.GlobalAveragePooling2D(),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])
model.compile(
    optimizer='adam',
    loss='sparse_categorical_crossentropy',
    metrics=['accuracy']
)

history = model.fit(
    x_train, y_train,
    validation_data=(x_test, y_test),
    epochs=2,
    batch_size=64,
    verbose=1
)
loss, acc = model.evaluate(x_test, y_test, verbose=0)
print(f"\n └ Test Accuracy: {acc:.4f}")
plt.figure(figsize=(10,4))
plt.subplot(1,2,1)
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.subplot(1,2,2)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Val Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.legend()
plt.tight_layout()
plt.show()
```

```
/tmp/ipython-input-1693943737.py:18: UserWarning: `input_shape` is undefined or non-square, or `rows` is not in [96, 128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the default.
  base_model = tf.keras.applications.MobileNetV2(
Downloaded data from https://storage.googleapis.com/tensorflow/keras-applications/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h5
9406464/9406464 0s 0us/step
Epoch 1/2
157/157 43s 239ms/step - accuracy: 0.3827 - loss: 1.8126 - val_accuracy: 0.6035 - val_loss: 1.1824
Epoch 2/2
157/157 40s 257ms/step - accuracy: 0.6609 - loss: 1.0089 - val_accuracy: 0.6180 - val_loss: 1.1267
```

Test Accuracy: 0.6180

