brain-tumor-classification-cnn-97-accuracy

July 17, 2025

0.0.1 import Dependence

[37]:
```
import warnings
warnings.filterwarnings('ignore')
```

[38]:
```
import shutil
import os
import random
import cv2
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from itertools import cycle
from tqdm.auto import tqdm
from pathlib import Path
from sklearn.utils import resample
from sklearn.utils import shuffle
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers , regularizers
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import load_model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.callbacks import EarlyStopping, ModelCheckpoint
from tensorflow.keras.layers import Dense,Activation,Dropout,Conv2D
from tensorflow.keras.layers import MaxPooling2D,BatchNormalization, Flatten
from tensorflow.keras.applications import ResNet50V2, VGG16, VGG19, MobileNetV2
from tensorflow.keras.applications.resnet_v2 import preprocess_input as␣
↪preprocess_resnet50v2
from tensorflow.keras.applications.vgg16 import preprocess_input as␣
↪preprocess_vgg16
from tensorflow.keras.applications.vgg19 import preprocess_input as␣
↪preprocess_vgg19
from tensorflow.keras.applications.mobilenet_v2 import preprocess_input as␣
↪preprocess_mobilenetv2
```

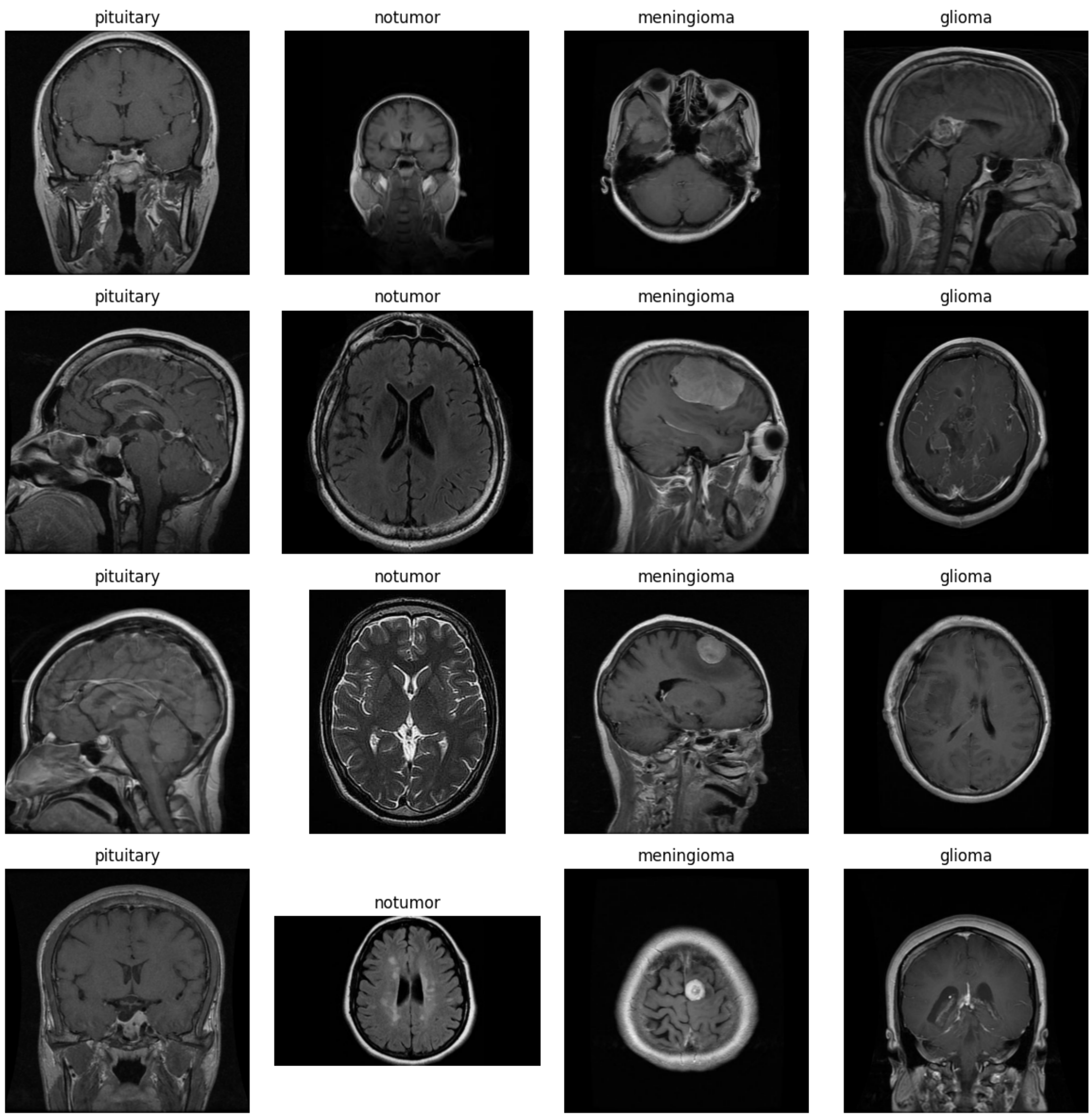
```
from tensorflow.keras.applications import EfficientNetB3
from tensorflow.keras.applications.efficientnet import preprocess_input as␣
↪efficientnet_preprocess
from tensorflow.keras.utils import to_categorical
```

0.0.2 Load Dataset

[39]:
```
train_path = '/kaggle/input/brain-tumor-mri-dataset/Training'
test_path = '/kaggle/input/brain-tumor-mri-dataset/Testing'
```

[40]:
```
main_folder = r'/kaggle/input/brain-tumor-mri-dataset/Training'
subfolders = [f for f in os.listdir(main_folder) if os.path.isdir(os.path.
↪join(main_folder, f))]

#Get images grouped by folder

folder_images = {}
for folder in subfolders:
    path = os.path.join(main_folder, folder)
    images = [os.path.join(path, img) for img in os.listdir(path) if img.
↪endswith(('.jpg','.png','.webp'))]
    random.shuffle(images) #Shuffle image within each folder
    folder_images[folder]= images

#Round-robin selection
selected_images=[]
folder_cycle = cycle(subfolders) # infinte loop through folders
while len(selected_images)<16:
    folder = next(folder_cycle)
    if folder_images[folder]: #if folder still has images
        selected_images.append(folder_images[folder].pop())
```

[41]:
```
#plot them
plt.figure(figsize=(12,12))
for i, img_path in enumerate(selected_images):
    img = cv2.imread(img_path)
    if img is None:
        continue
    img = cv2.cvtColor(img,cv2.COLOR_BGR2RGB)
    plt.subplot(4,4,i+1)
    plt.imshow(img, cmap='gray')
    plt.axis('off')
    plt.title(os.path.basename(os.path.dirname(img_path))) #show folder name
plt.tight_layout()
plt.show()
```



[42]:
```
ain_folder = r'/kaggle/input/brain-tumor-mri-dataset/Testing'
subfolders = [f for f in os.listdir(main_folder) if os.path.isdir(os.path.
 ↪join(main_folder, f))]

# Get images grouped by folder
folder_images = {}
for folder in subfolders:
    path = os.path.join(main_folder, folder)
    images = [os.path.join(path, img) for img in os.listdir(path)
              if img.endswith(('.jpg', '.png', '.webp'))]
    random.shuffle(images)  # Shuffle images within each folder
    folder_images[folder] = images
```

```
# Round-robin selection
selected_images = []
folder_cycle = cycle(subfolders)  # Infinite loop through folders
while len(selected_images) < 16:
    folder = next(folder_cycle)
    if folder_images[folder]:  # If folder still has images
        selected_images.append(folder_images[folder].pop())
```

0.0.3 Data Preprocessing

[45]:
```
IMAGE_SIZE = 224
BATCH_SIZE = 32
```

[46]:
```
def cnn_preprocess(x):
    return x/255.0
```

[47]:
```
cnn_train_datagen = ImageDataGenerator(preprocessing_function=cnn_preprocess)
cnn_train_generator = cnn_train_datagen.flow_from_directory(
    train_path,
    target_size =(IMAGE_SIZE, IMAGE_SIZE),
    batch_size = BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 5712 images belonging to 4 classes.
```

[48]:
```
cnn_train_generator.class_indices
```

[48]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[49]:
```
cnn_test_datagen = ImageDataGenerator(preprocessing_function= cnn_preprocess)
cnn_test_generator = cnn_test_datagen.flow_from_directory(
    test_path,
    target_size=(IMAGE_SIZE,IMAGE_SIZE),
    batch_size= BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 1311 images belonging to 4 classes.
```

[50]:
```
cnn_test_generator.class_indices
```

[50]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

0.0.4 CNN Model Building

[13]:
```
cnn_model = keras.Sequential([

    Conv2D(filters=64, kernel_size=(3,3),padding="same",
    activation='relu', input_shape= (IMAGE_SIZE,IMAGE_SIZE,3)),
    Conv2D(filters=64, kernel_size=(3,3),padding="same",
    activation='relu', input_shape= (IMAGE_SIZE,IMAGE_SIZE,3)),
    MaxPooling2D(pool_size=(2,2)),

    Conv2D(filters=128, kernel_size=(3,3),padding="same",
    activation='relu', input_shape= (IMAGE_SIZE,IMAGE_SIZE,3)),
    Conv2D(filters=128, kernel_size=(3,3),padding="same",
    activation='relu', input_shape= (IMAGE_SIZE,IMAGE_SIZE,3)),
    MaxPooling2D(pool_size=(2,2)),

    Conv2D(filters=256, kernel_size=(3,3),padding="same",
    activation='relu', input_shape= (IMAGE_SIZE,IMAGE_SIZE,3)),
    MaxPooling2D(pool_size=(2, 2)),

    Flatten(),
    Dropout(0.4),

    Dense(256,activation='relu'),
    Dense(128,activation='relu'),
    Dense(64,activation='relu'),

    Dense(units=len(cnn_test_generator.class_indices), activation='softmax',
 ↪dtype='float32')

])
```

```
I0000 00:00:1752732486.406753      36 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 15513 MB memory:  -> device:
0, name: Tesla P100-PCIE-16GB, pci bus id: 0000:00:04.0, compute capability: 6.0
```

[14]:
```
cnn_model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 224, 224, 64)	1,792
conv2d_1 (Conv2D)	(None, 224, 224, 64)	36,928
max_pooling2d (MaxPooling2D)	(None, 112, 112, 64)	0

conv2d_2 (Conv2D)	(None, 112, 112, 128)	73,856
conv2d_3 (Conv2D)	(None, 112, 112, 128)	147,584
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 128)	0
conv2d_4 (Conv2D)	(None, 56, 56, 256)	295,168
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 256)	0
flatten (Flatten)	(None, 200704)	0
dropout (Dropout)	(None, 200704)	0
dense (Dense)	(None, 256)	51,380,480
dense_1 (Dense)	(None, 128)	32,896
dense_2 (Dense)	(None, 64)	8,256
dense_3 (Dense)	(None, 4)	260

Total params: 51,977,220 (198.28 MB)

Trainable params: 51,977,220 (198.28 MB)

Non-trainable params: 0 (0.00 B)

[15]:
```
callbacks = [
    EarlyStopping(
        monitor='val_loss',
        patience=5,
        restore_best_weights=True
    ),

    ModelCheckpoint(
        filepath='CCN.h5',
        monitor='val_loss',
        save_best_only=True,
        save_weights_only=False,
        mode='min',
        verbose=1
    ),
```

```
    keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=3,
        min_lr=1e-7,
        verbose=1
    )
]
```

[16]:
```
cnn_model.compile(optimizer=keras.optimizers.Adam(learning_rate=0.0001),
                  loss='categorical_crossentropy',metrics=['accuracy',keras.
 ↪metrics.Precision(name='precision'),
                                    keras.metrics.Recall(name='recall'),
                                    keras.metrics.F1Score(name='f1_score')
                                                          ])
```

[17]:
```
cnn_history = cnn_model.fit(
    cnn_train_generator,
    epochs= 20,
    validation_data = cnn_test_generator,
    callbacks = callbacks
)
```

```
Epoch 1/20

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1752732493.546379     111 service.cc:148] XLA service 0x7af9780051e0
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1752732493.547169     111 service.cc:156]   StreamExecutor device
(0): Tesla P100-PCIE-16GB, Compute Capability 6.0
I0000 00:00:1752732494.079301     111 cuda_dnn.cc:529] Loaded cuDNN version
90300

  1/179              57:03 19s/step - accuracy:
0.1875 - f1_score: 0.0909 - loss: 1.3886 - precision: 0.0000e+00 - recall:
0.0000e+00

I0000 00:00:1752732507.565430     111 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

179/179              0s 264ms/step -
accuracy: 0.5474 - f1_score: 0.5045 - loss: 0.9567 - precision: 0.8012 - recall:
0.3867
Epoch 1: val_loss improved from inf to 0.67515, saving model to CCN.h5
179/179              87s 379ms/step -
accuracy: 0.5482 - f1_score: 0.5054 - loss: 0.9555 - precision: 0.8012 - recall:
0.3878 - val_accuracy: 0.7620 - val_f1_score: 0.7207 - val_loss: 0.6752 -
val_precision: 0.7746 - val_recall: 0.7445 - learning_rate: 1.0000e-04
```

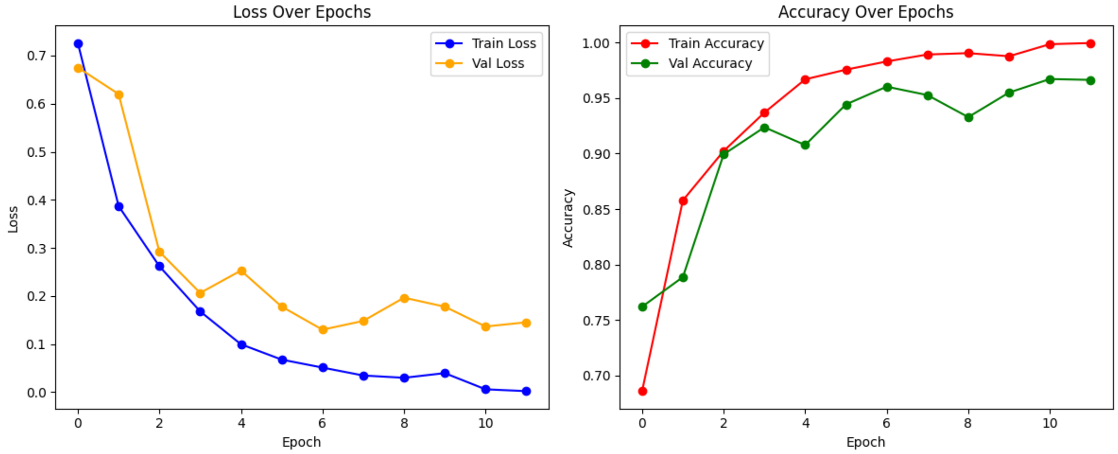
```
Epoch 2/20
179/179              0s 120ms/step -
accuracy: 0.8492 - f1_score: 0.8422 - loss: 0.4222 - precision: 0.8637 - recall:
0.8244
Epoch 2: val_loss improved from 0.67515 to 0.61997, saving model to CCN.h5
179/179              27s 152ms/step -
accuracy: 0.8493 - f1_score: 0.8422 - loss: 0.4220 - precision: 0.8638 - recall:
0.8245 - val_accuracy: 0.7887 - val_f1_score: 0.7626 - val_loss: 0.6200 -
val_precision: 0.8098 - val_recall: 0.7727 - learning_rate: 1.0000e-04
Epoch 3/20
179/179              0s 119ms/step -
accuracy: 0.8944 - f1_score: 0.8897 - loss: 0.2778 - precision: 0.9042 - recall:
0.8847
Epoch 3: val_loss improved from 0.61997 to 0.29215, saving model to CCN.h5
179/179              27s 152ms/step -
accuracy: 0.8944 - f1_score: 0.8898 - loss: 0.2777 - precision: 0.9043 - recall:
0.8848 - val_accuracy: 0.8993 - val_f1_score: 0.8968 - val_loss: 0.2922 -
val_precision: 0.9022 - val_recall: 0.8940 - learning_rate: 1.0000e-04
Epoch 4/20
179/179              0s 119ms/step -
accuracy: 0.9307 - f1_score: 0.9287 - loss: 0.1883 - precision: 0.9347 - recall:
0.9263
Epoch 4: val_loss improved from 0.29215 to 0.20643, saving model to CCN.h5
179/179              28s 154ms/step -
accuracy: 0.9307 - f1_score: 0.9287 - loss: 0.1882 - precision: 0.9347 - recall:
0.9263 - val_accuracy: 0.9237 - val_f1_score: 0.9189 - val_loss: 0.2064 -
val_precision: 0.9276 - val_recall: 0.9191 - learning_rate: 1.0000e-04
Epoch 5/20
179/179              0s 119ms/step -
accuracy: 0.9694 - f1_score: 0.9678 - loss: 0.0952 - precision: 0.9706 - recall:
0.9685
Epoch 5: val_loss did not improve from 0.20643
179/179              25s 139ms/step -
accuracy: 0.9694 - f1_score: 0.9678 - loss: 0.0952 - precision: 0.9706 - recall:
0.9685 - val_accuracy: 0.9077 - val_f1_score: 0.9005 - val_loss: 0.2529 -
val_precision: 0.9134 - val_recall: 0.9008 - learning_rate: 1.0000e-04
Epoch 6/20
179/179              0s 121ms/step -
accuracy: 0.9754 - f1_score: 0.9737 - loss: 0.0680 - precision: 0.9754 - recall:
0.9739
Epoch 6: val_loss improved from 0.20643 to 0.17794, saving model to CCN.h5
179/179              28s 155ms/step -
accuracy: 0.9754 - f1_score: 0.9737 - loss: 0.0680 - precision: 0.9754 - recall:
0.9739 - val_accuracy: 0.9443 - val_f1_score: 0.9405 - val_loss: 0.1779 -
val_precision: 0.9443 - val_recall: 0.9443 - learning_rate: 1.0000e-04
Epoch 7/20
179/179              0s 120ms/step -
accuracy: 0.9877 - f1_score: 0.9873 - loss: 0.0441 - precision: 0.9877 - recall:
```

```
0.9872
Epoch 7: val_loss improved from 0.17794 to 0.12999, saving model to CCN.h5
179/179            28s 153ms/step -
accuracy: 0.9877 - f1_score: 0.9872 - loss: 0.0441 - precision: 0.9877 - recall:
0.9871 - val_accuracy: 0.9603 - val_f1_score: 0.9575 - val_loss: 0.1300 -
val_precision: 0.9625 - val_recall: 0.9603 - learning_rate: 1.0000e-04
Epoch 8/20
179/179            0s 120ms/step -
accuracy: 0.9928 - f1_score: 0.9925 - loss: 0.0243 - precision: 0.9929 - recall:
0.9927
Epoch 8: val_loss did not improve from 0.12999
179/179            25s 139ms/step -
accuracy: 0.9928 - f1_score: 0.9925 - loss: 0.0244 - precision: 0.9929 - recall:
0.9926 - val_accuracy: 0.9527 - val_f1_score: 0.9487 - val_loss: 0.1482 -
val_precision: 0.9527 - val_recall: 0.9519 - learning_rate: 1.0000e-04
Epoch 9/20
179/179            0s 119ms/step -
accuracy: 0.9925 - f1_score: 0.9922 - loss: 0.0257 - precision: 0.9925 - recall:
0.9925
Epoch 9: val_loss did not improve from 0.12999
179/179            25s 138ms/step -
accuracy: 0.9925 - f1_score: 0.9922 - loss: 0.0257 - precision: 0.9925 - recall:
0.9925 - val_accuracy: 0.9329 - val_f1_score: 0.9290 - val_loss: 0.1965 -
val_precision: 0.9349 - val_recall: 0.9306 - learning_rate: 1.0000e-04
Epoch 10/20
179/179            0s 120ms/step -
accuracy: 0.9864 - f1_score: 0.9861 - loss: 0.0439 - precision: 0.9864 - recall:
0.9862
Epoch 10: val_loss did not improve from 0.12999

Epoch 10: ReduceLROnPlateau reducing learning rate to 4.999999873689376e-05.
179/179            25s 138ms/step -
accuracy: 0.9864 - f1_score: 0.9861 - loss: 0.0439 - precision: 0.9864 - recall:
0.9862 - val_accuracy: 0.9550 - val_f1_score: 0.9522 - val_loss: 0.1779 -
val_precision: 0.9550 - val_recall: 0.9550 - learning_rate: 1.0000e-04
Epoch 11/20
179/179            0s 119ms/step -
accuracy: 0.9975 - f1_score: 0.9975 - loss: 0.0089 - precision: 0.9975 - recall:
0.9975
Epoch 11: val_loss did not improve from 0.12999
179/179            25s 137ms/step -
accuracy: 0.9975 - f1_score: 0.9975 - loss: 0.0089 - precision: 0.9975 - recall:
0.9975 - val_accuracy: 0.9672 - val_f1_score: 0.9650 - val_loss: 0.1366 -
val_precision: 0.9672 - val_recall: 0.9672 - learning_rate: 5.0000e-05
Epoch 12/20
179/179            0s 119ms/step -
accuracy: 0.9999 - f1_score: 0.9999 - loss: 0.0023 - precision: 0.9999 - recall:
0.9999
```

```
Epoch 12: val_loss did not improve from 0.12999
179/179              25s 137ms/step -
accuracy: 0.9999 - f1_score: 0.9999 - loss: 0.0023 - precision: 0.9999 - recall:
0.9999 - val_accuracy: 0.9664 - val_f1_score: 0.9645 - val_loss: 0.1454 -
val_precision: 0.9672 - val_recall: 0.9664 - learning_rate: 5.0000e-05
```

[18]:

```
#Plotting training and validation loss and accuracy
plt.figure(figsize=(12, 5))

#   Loss
plt.subplot(1, 2, 1)
plt.plot(cnn_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
plt.plot(cnn_history.history['val_loss'], label='Val Loss', marker='o',␣
 ↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

#   Accuracy
plt.subplot(1, 2, 2)
plt.plot(cnn_history.history['accuracy'], label='Train Accuracy', marker='o',␣
 ↪color='red')
plt.plot(cnn_history.history['val_accuracy'], label='Val Accuracy', marker='o',␣
 ↪color='green')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[51]:
```python
def merge_brain_tumor_dataset(base_path, output_path):

    # Define the class names (subfolder names)
    classes = ['glioma_tumor', 'meningioma_tumor', 'no_tumor',␣
↪'pituitary_tumor']

    # Create output directory structure
    os.makedirs(output_path, exist_ok=True)

    for class_name in classes:
        class_output_dir = os.path.join(output_path, class_name)
        os.makedirs(class_output_dir, exist_ok=True)
        print(f"Created directory: {class_output_dir}")

    # Copy files from Training and Testing folders
    for folder_type in ['Training', 'Testing']:
        folder_path = os.path.join(base_path, folder_type)

        if not os.path.exists(folder_path):
            print(f"Warning: {folder_path} does not exist!")
            continue

        print(f"\nProcessing {folder_type} folder...")

        for class_name in classes:
            source_dir = os.path.join(folder_path, class_name)
            target_dir = os.path.join(output_path, class_name)

            if not os.path.exists(source_dir):
                print(f"Warning: {source_dir} does not exist!")
                continue

            # Get all image files from source directory
            image_files = [f for f in os.listdir(source_dir)
                           if f.lower().endswith(('.png', '.jpg', '.jpeg', '.
↪bmp', '.tiff'))]

            print(f"  {class_name}: Found {len(image_files)} images")

            # Copy each image file
            for i, filename in enumerate(image_files):
                source_file = os.path.join(source_dir, filename)

                # Add prefix to avoid naming conflicts
```

```
                new_filename = f"{folder_type.lower()}_{filename}"
                target_file = os.path.join(target_dir, new_filename)

                try:
                    shutil.copy2(source_file, target_file)
                except Exception as e:
                    print(f"Error copying {source_file}: {e}")

            print(f"  Copied {len(image_files)} images from {class_name}")

    # Print final statistics
    print("\n" + "="*50)
    print("MERGE COMPLETE - Final Statistics:")
    print("="*50)

    total_images = 0
    for class_name in classes:
        class_dir = os.path.join(output_path, class_name)
        if os.path.exists(class_dir):
            count = len([f for f in os.listdir(class_dir)
                        if f.lower().endswith(('.png', '.jpg', '.jpeg', '.bmp',␣
 ↪'.tiff'))])
            print(f"{class_name}: {count} images")
            total_images += count

    print(f"\nTotal images in merged dataset: {total_images}")
    print(f"Merged dataset saved to: {output_path}")

# Path to dataset ()
dataset_path = "/kaggle/input/brain-tumor-classification-mri"

output_path = "/kaggle/working/merged_brain_tumor_dataset"

# Run the merge function
merge_brain_tumor_dataset(dataset_path, output_path)

print("\n" + "="*50)
print("Sample files from merged dataset:")
print("="*50)

for class_name in ['glioma_tumor', 'meningioma_tumor', 'no_tumor',␣
 ↪'pituitary_tumor']:
    class_dir = os.path.join(output_path, class_name)
    if os.path.exists(class_dir):
        files = os.listdir(class_dir)[:3]  # Show first 3 files
        print(f"\n{class_name} (showing first 3 files):")
        for file in files:
```

```
            print(f"  - {file}")
```

```
Created directory: /kaggle/working/merged_brain_tumor_dataset/glioma_tumor
Created directory: /kaggle/working/merged_brain_tumor_dataset/meningioma_tumor
Created directory: /kaggle/working/merged_brain_tumor_dataset/no_tumor
Created directory: /kaggle/working/merged_brain_tumor_dataset/pituitary_tumor

Processing Training folder…
  glioma_tumor: Found 826 images
  Copied 826 images from glioma_tumor
  meningioma_tumor: Found 822 images
  Copied 822 images from meningioma_tumor
  no_tumor: Found 395 images
  Copied 395 images from no_tumor
  pituitary_tumor: Found 827 images
  Copied 827 images from pituitary_tumor

Processing Testing folder…
  glioma_tumor: Found 100 images
  Copied 100 images from glioma_tumor
  meningioma_tumor: Found 115 images
  Copied 115 images from meningioma_tumor
  no_tumor: Found 105 images
  Copied 105 images from no_tumor
  pituitary_tumor: Found 74 images
  Copied 74 images from pituitary_tumor

==================================================
MERGE COMPLETE - Final Statistics:
==================================================
glioma_tumor: 926 images
meningioma_tumor: 937 images
no_tumor: 500 images
pituitary_tumor: 901 images

Total images in merged dataset: 3264
Merged dataset saved to: /kaggle/working/merged_brain_tumor_dataset

==================================================
Sample files from merged dataset:
==================================================

glioma_tumor (showing first 3 files):
  - training_gg (508).jpg
  - training_gg (207).jpg
  - training_gg (427).jpg

meningioma_tumor (showing first 3 files):
```

```
  - training_m1(38).jpg
  - training_m3 (186).jpg
  - training_m2 (109).jpg

no_tumor (showing first 3 files):
  - training_image(253).jpg
  - testing_image(91).jpg
  - testing_image(32).jpg

pituitary_tumor (showing first 3 files):
  - testing_image(91).jpg
  - training_p (170).jpg
  - training_p (54).jpg
```

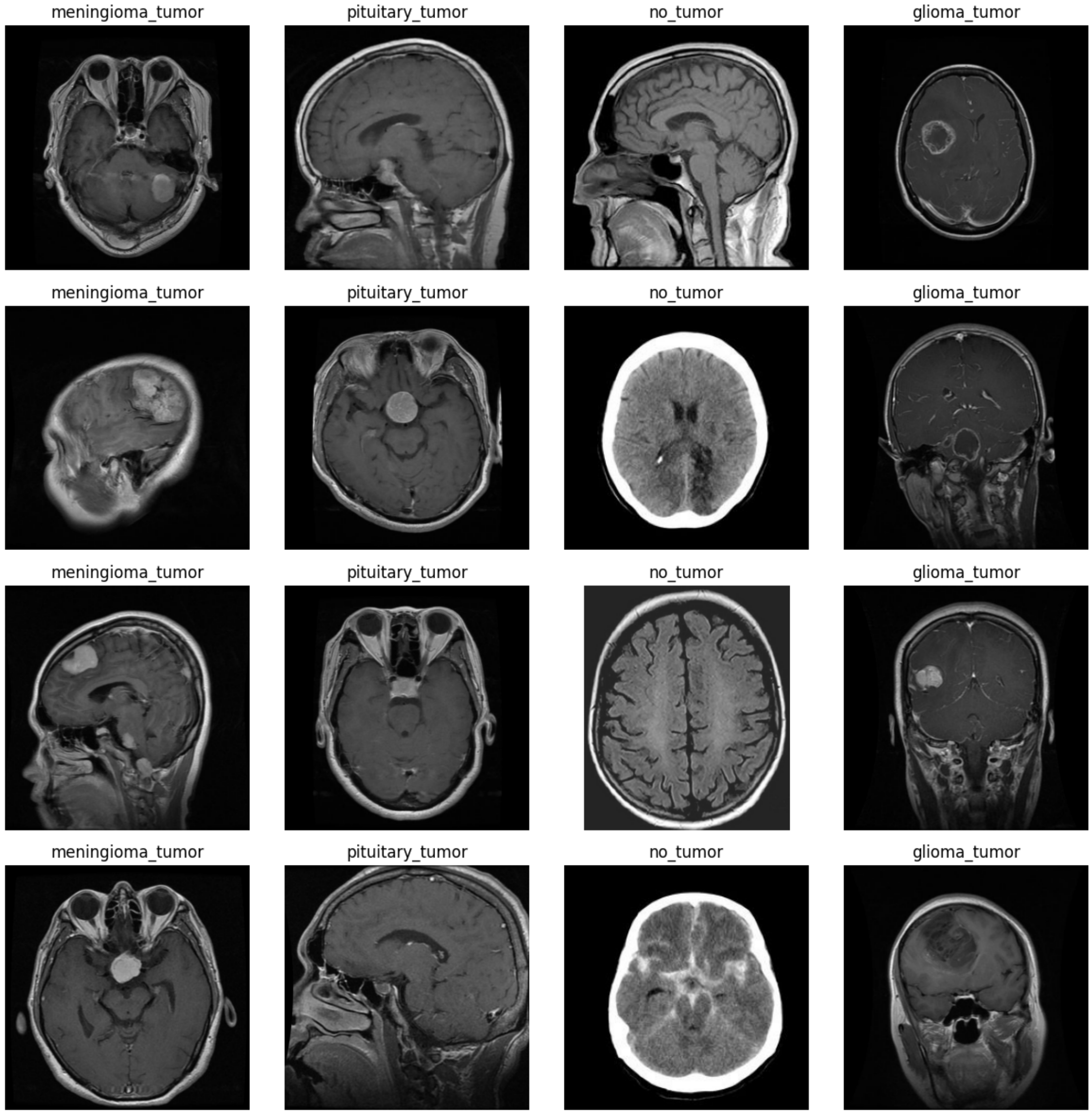
[52]:
```
test_path_1 = '/kaggle/working/merged_brain_tumor_dataset'
```

[53]:
```
dataset_path = "/kaggle/working/merged_brain_tumor_dataset"
output_path = "/kaggle/working/merged_brain_tumor_dataset"

# Get file lists for each class
glioma_files = os.listdir(f"{dataset_path}/glioma_tumor")
meningioma_files = os.listdir(f"{dataset_path}/meningioma_tumor")
no_tumor_files = os.listdir(f"{dataset_path}/no_tumor")
pituitary_files = os.listdir(f"{dataset_path}/pituitary_tumor")

print("Original distribution:")
print(f"glioma_tumor: {len(glioma_files)}")
print(f"meningioma_tumor: {len(meningioma_files)}")
print(f"no_tumor: {len(no_tumor_files)}")
print(f"pituitary_tumor: {len(pituitary_files)}")

# Find minimum class size
min_size = min(len(glioma_files), len(meningioma_files), len(no_tumor_files),␣
↪len(pituitary_files))
print(f"\nDownsampling all to: {min_size} samples")

# Downsample each class
# Downsample each class
glioma_downsampled = resample(glioma_files,
                              replace=False,
                              n_samples=min_size,
                              random_state=42)

meningioma_downsampled = resample(meningioma_files,
                                  replace=False,
                                  n_samples=min_size,
                                  random_state=42)
```

```
no_tumor_downsampled = resample(no_tumor_files,
                               replace=False,
                               n_samples=min_size,
                               random_state=42)

pituitary_downsampled = resample(pituitary_files,
                                replace=False,
                                n_samples=min_size,
                                random_state=42)

# Keep only the downsampled files (delete the rest)
classes = {
    'glioma_tumor': glioma_downsampled,
    'meningioma_tumor': meningioma_downsampled,
    'no_tumor': no_tumor_downsampled,
    'pituitary_tumor': pituitary_downsampled
}

for class_name, keep_files in classes.items():
    class_dir = f"{dataset_path}/{class_name}"
    all_files = os.listdir(class_dir)

    # Delete files that are NOT in the downsampled list
    for filename in all_files:
        if filename not in keep_files:
            file_path = f"{class_dir}/{filename}"
            os.remove(file_path)

    remaining = len(os.listdir(class_dir))
    print(f"{class_name}: kept {remaining} files")

print("Done!")
```

```
Original distribution:
glioma_tumor: 926
meningioma_tumor: 937
no_tumor: 500
pituitary_tumor: 901

Downsampling all to: 500 samples
glioma_tumor: kept 500 files
meningioma_tumor: kept 500 files
no_tumor: kept 500 files
pituitary_tumor: kept 500 files
Done!
```

[54]:
```
main_folder = r'/kaggle/working/merged_brain_tumor_dataset'
subfolders = [f for f in os.listdir(main_folder) if os.path.isdir(os.path.
 ↪join(main_folder, f))]

# Get images grouped by folder
folder_images = {}
for folder in subfolders:
    path = os.path.join(main_folder, folder)
    images = [os.path.join(path, img) for img in os.listdir(path)
              if img.endswith(('.jpg', '.png', '.webp'))]
    random.shuffle(images)  # Shuffle images within each folder
    folder_images[folder] = images

# Round-robin selection
selected_images = []
folder_cycle = cycle(subfolders)  # Infinite loop through folders
while len(selected_images) < 16:
    folder = next(folder_cycle)
    if folder_images[folder]:  # If folder still has images
        selected_images.append(folder_images[folder].pop())

# Plot them
plt.figure(figsize=(12, 12))
for i, img_path in enumerate(selected_images):
    img = cv2.imread(img_path)
    if img is None:
        continue
    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    plt.subplot(4, 4, i + 1)
    plt.imshow(img, cmap='gray')
    plt.axis('off')
    plt.title(os.path.basename(os.path.dirname(img_path)))  # Show folder name
plt.tight_layout()
plt.show()
```



[55]:
```
cnn_merged_datagen = ImageDataGenerator(preprocessing_function=cnn_preprocess)
cnn_merged_generator = cnn_merged_datagen.flow_from_directory(
        output_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

```
Found 2000 images belonging to 4 classes.
```

[24]:
```
cnn_predictions = cnn_model.predict(cnn_merged_generator)
```

```
63/63                  7s 103ms/step
```

[25]:
```
cnn_result = cnn_model.evaluate(cnn_merged_generator, batch_size=BATCH_SIZE)
print('Loss: ',cnn_result[0])
print('Accuracy: ',cnn_result[1])
```

```
63/63              5s 71ms/step -
accuracy: 0.9050 - f1_score: 0.8988 - loss: 0.6842 - precision: 0.9069 - recall:
0.9037
Loss:  0.7615350484848022
Accuracy:  0.8934999704360962
```

0.0.5 VGG16 Model

[56]:
```
def preprocess_vgg16(x):
    return x/255.0
```

[57]:
```
VGG16_train_datagen =␣
↪ImageDataGenerator(preprocessing_function=preprocess_vgg16)
VGG16_train_generator = VGG16_train_datagen.flow_from_directory(
    train_path,
    target_size=(IMAGE_SIZE,IMAGE_SIZE),
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 5712 images belonging to 4 classes.
```

[58]:
```
VGG16_train_generator.class_indices
```

[58]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[59]:
```
VGG16_test_datagen = ImageDataGenerator(preprocessing_function=preprocess_vgg16)
VGG16_test_generator = VGG16_test_datagen.flow_from_directory(
        test_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

```
Found 1311 images belonging to 4 classes.
```

[60]:
```
VGG16_test_generator.class_indices
```

[60]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[61]:
```
trained_VGG16_layers =␣
↪VGG16(weights='imagenet',include_top=False,input_shape=(IMAGE_SIZE,IMAGE_SIZE,3))
```

[62]:
```
for layer in trained_VGG16_layers.layers:
    layer.trainable = False
```

[63]:
```
VGG16_model = keras.models.Sequential([
    trained_VGG16_layers,
    Flatten(),
    Dense(256,activation='relu'),
    Dense(4,activation='softmax')
])
```

[64]:
```
VGG16_model.summary()
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
vgg16 (Functional)	(None, 7, 7, 512)	14,714,688
flatten_2 (Flatten)	(None, 25088)	0
dense_6 (Dense)	(None, 256)	6,422,784
dense_7 (Dense)	(None, 4)	1,028

Total params: 21,138,500 (80.64 MB)

Trainable params: 6,423,812 (24.50 MB)

Non-trainable params: 14,714,688 (56.13 MB)

[65]:
```
VGG16_model.
↪compile(optimizer='Adam',loss='categorical_crossentropy',metrics=['accuracy'])
```

[66]:
```
VGG16_history = VGG16_model.fit(
    VGG16_train_generator,
    epochs=20,
    validation_data = VGG16_test_generator,
    callbacks = callbacks
)
```

```
Epoch 1/20
179/179              0s 84ms/step -
accuracy: 0.7236 - loss: 1.1928
Epoch 1: val_loss did not improve from 0.07422
179/179              23s 111ms/step -
accuracy: 0.7242 - loss: 1.1892 - val_accuracy: 0.9001 - val_loss: 0.2461 -
```

```
learning_rate: 0.0010
Epoch 2/20
179/179            0s 83ms/step -
accuracy: 0.9213 - loss: 0.2069
Epoch 2: val_loss did not improve from 0.07422
179/179            18s 103ms/step -
accuracy: 0.9213 - loss: 0.2068 - val_accuracy: 0.9169 - val_loss: 0.2070 -
learning_rate: 0.0010
Epoch 3/20
179/179            0s 86ms/step -
accuracy: 0.9560 - loss: 0.1151
Epoch 3: val_loss did not improve from 0.07422
179/179            19s 106ms/step -
accuracy: 0.9560 - loss: 0.1151 - val_accuracy: 0.8955 - val_loss: 0.2978 -
learning_rate: 0.0010
Epoch 4/20
179/179            0s 85ms/step -
accuracy: 0.9641 - loss: 0.0937
Epoch 4: val_loss did not improve from 0.07422
179/179            19s 104ms/step -
accuracy: 0.9642 - loss: 0.0936 - val_accuracy: 0.9565 - val_loss: 0.1083 -
learning_rate: 0.0010
Epoch 5/20
179/179            0s 83ms/step -
accuracy: 0.9857 - loss: 0.0429
Epoch 5: val_loss did not improve from 0.07422
179/179            18s 102ms/step -
accuracy: 0.9857 - loss: 0.0429 - val_accuracy: 0.9657 - val_loss: 0.0883 -
learning_rate: 0.0010
Epoch 6/20
179/179            0s 81ms/step -
accuracy: 0.9933 - loss: 0.0291
Epoch 6: val_loss did not improve from 0.07422
179/179            18s 100ms/step -
accuracy: 0.9933 - loss: 0.0292 - val_accuracy: 0.9580 - val_loss: 0.1077 -
learning_rate: 0.0010
Epoch 7/20
179/179            0s 78ms/step -
accuracy: 0.9983 - loss: 0.0177
Epoch 7: val_loss did not improve from 0.07422
179/179            17s 96ms/step -
accuracy: 0.9983 - loss: 0.0177 - val_accuracy: 0.9573 - val_loss: 0.1323 -
learning_rate: 0.0010
Epoch 8/20
179/179            0s 79ms/step -
accuracy: 0.9848 - loss: 0.0449
Epoch 8: val_loss did not improve from 0.07422
```

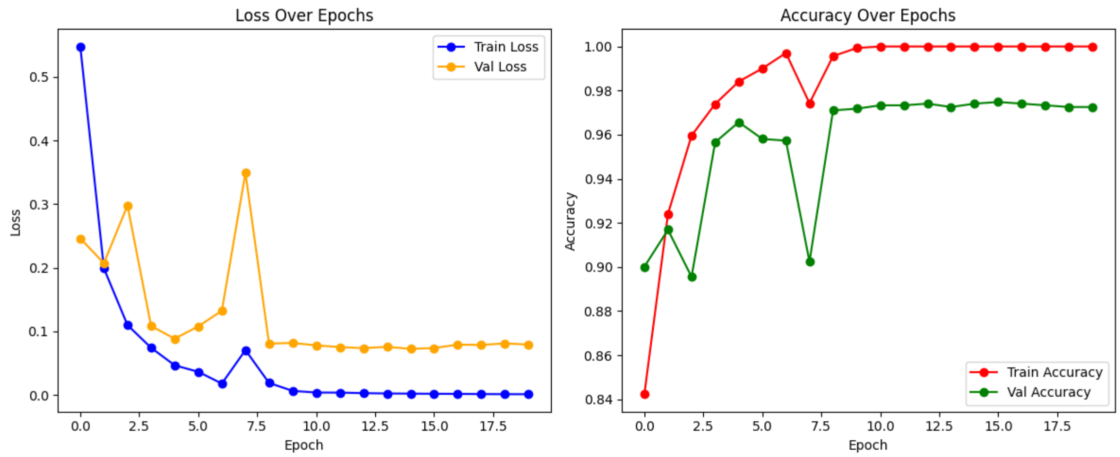
```
Epoch 8: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
179/179            18s 98ms/step -
accuracy: 0.9847 - loss: 0.0451 - val_accuracy: 0.9024 - val_loss: 0.3492 -
learning_rate: 0.0010
Epoch 9/20
179/179            0s 85ms/step -
accuracy: 0.9917 - loss: 0.0338
Epoch 9: val_loss did not improve from 0.07422
179/179            18s 102ms/step -
accuracy: 0.9917 - loss: 0.0337 - val_accuracy: 0.9710 - val_loss: 0.0806 -
learning_rate: 5.0000e-04
Epoch 10/20
179/179            0s 83ms/step -
accuracy: 0.9988 - loss: 0.0065
Epoch 10: val_loss did not improve from 0.07422
179/179            18s 101ms/step -
accuracy: 0.9988 - loss: 0.0065 - val_accuracy: 0.9718 - val_loss: 0.0816 -
learning_rate: 5.0000e-04
Epoch 11/20
179/179            0s 80ms/step -
accuracy: 1.0000 - loss: 0.0035
Epoch 11: val_loss did not improve from 0.07422
179/179            18s 100ms/step -
accuracy: 1.0000 - loss: 0.0035 - val_accuracy: 0.9733 - val_loss: 0.0779 -
learning_rate: 5.0000e-04
Epoch 12/20
179/179            0s 83ms/step -
accuracy: 1.0000 - loss: 0.0036
Epoch 12: val_loss did not improve from 0.07422
179/179            18s 102ms/step -
accuracy: 1.0000 - loss: 0.0036 - val_accuracy: 0.9733 - val_loss: 0.0751 -
learning_rate: 5.0000e-04
Epoch 13/20
179/179            0s 80ms/step -
accuracy: 1.0000 - loss: 0.0029
Epoch 13: val_loss improved from 0.07422 to 0.07353, saving model to CCN.h5
179/179            18s 100ms/step -
accuracy: 1.0000 - loss: 0.0029 - val_accuracy: 0.9741 - val_loss: 0.0735 -
learning_rate: 5.0000e-04
Epoch 14/20
179/179            0s 78ms/step -
accuracy: 1.0000 - loss: 0.0021
Epoch 14: val_loss did not improve from 0.07353
179/179            17s 96ms/step -
accuracy: 1.0000 - loss: 0.0021 - val_accuracy: 0.9725 - val_loss: 0.0755 -
learning_rate: 5.0000e-04
Epoch 15/20
179/179            0s 85ms/step -
```

```
accuracy: 1.0000 - loss: 0.0017
Epoch 15: val_loss improved from 0.07353 to 0.07241, saving model to CCN.h5
179/179              19s 105ms/step -
accuracy: 1.0000 - loss: 0.0017 - val_accuracy: 0.9741 - val_loss: 0.0724 -
learning_rate: 5.0000e-04
Epoch 16/20
179/179              0s 82ms/step -
accuracy: 1.0000 - loss: 0.0016
Epoch 16: val_loss did not improve from 0.07241
179/179              18s 100ms/step -
accuracy: 1.0000 - loss: 0.0016 - val_accuracy: 0.9748 - val_loss: 0.0736 -
learning_rate: 5.0000e-04
Epoch 17/20
179/179              0s 82ms/step -
accuracy: 1.0000 - loss: 0.0016
Epoch 17: val_loss did not improve from 0.07241
179/179              18s 101ms/step -
accuracy: 1.0000 - loss: 0.0016 - val_accuracy: 0.9741 - val_loss: 0.0790 -
learning_rate: 5.0000e-04
Epoch 18/20
179/179              0s 84ms/step -
accuracy: 1.0000 - loss: 0.0012
Epoch 18: val_loss did not improve from 0.07241

Epoch 18: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
179/179              19s 104ms/step -
accuracy: 1.0000 - loss: 0.0012 - val_accuracy: 0.9733 - val_loss: 0.0785 -
learning_rate: 5.0000e-04
Epoch 19/20
179/179              0s 86ms/step -
accuracy: 1.0000 - loss: 0.0011
Epoch 19: val_loss did not improve from 0.07241
179/179              19s 106ms/step -
accuracy: 1.0000 - loss: 0.0011 - val_accuracy: 0.9725 - val_loss: 0.0809 -
learning_rate: 2.5000e-04
Epoch 20/20
179/179              0s 83ms/step -
accuracy: 1.0000 - loss: 0.0010
Epoch 20: val_loss did not improve from 0.07241
179/179              18s 102ms/step -
accuracy: 1.0000 - loss: 0.0010 - val_accuracy: 0.9725 - val_loss: 0.0791 -
learning_rate: 2.5000e-04
```

[67]:

```
# Plotting training and validation loss and accuracy

plt.figure(figsize=(12, 5))
```

```
#   Loss
plt.subplot(1, 2, 1)
plt.plot(VGG16_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
plt.plot(VGG16_history.history['val_loss'], label='Val Loss', marker='o',␣
 ↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

#   Accuracy
plt.subplot(1, 2, 2)
plt.plot(VGG16_history.history['accuracy'], label='Train Accuracy', marker='o',␣
 ↪color='red')
plt.plot(VGG16_history.history['val_accuracy'], label='Val Accuracy',␣
 ↪marker='o', color='green')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[68]:
```
vgg16_predictions = VGG16_model.predict(cnn_merged_generator)
```

```
63/63                 6s 81ms/step
```

[69]:
```
vgg16_result = VGG16_model.evaluate(cnn_merged_generator, batch_size =␣
 ↪BATCH_SIZE)
```

```
print('Accuracy: ',vgg16_result[1])
```

```
63/63              5s 80ms/step -
accuracy: 0.9398 - loss: 0.4743
Accuracy:  0.9330000281333923
```

0.0.6 VGG19 Model Building

[70]:
```
def preprocess_vgg19(x):
    return x/255.0
```

[71]:
```
VGG19_train_datagen =␣
 ↪ImageDataGenerator(preprocessing_function=preprocess_vgg19)
VGG19_train_generator = VGG19_train_datagen.flow_from_directory(
        train_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

```
Found 5712 images belonging to 4 classes.
```

[72]:
```
VGG19_train_generator.class_indices
```

[72]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[73]:
```
VGG19_test_datagen = ImageDataGenerator(preprocessing_function=preprocess_vgg19)
VGG19_test_generator = VGG19_test_datagen.flow_from_directory(
        test_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

```
Found 1311 images belonging to 4 classes.
```

[74]:
```
VGG19_test_generator.class_indices
```

[74]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[75]:
```
trained_VGG19_layers =␣
 ↪VGG19(weights='imagenet',include_top=False,input_shape=(IMAGE_SIZE,IMAGE_SIZE,3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/vgg19/vgg19_weights_tf_dim_ordering_tf_kernels_notop.h5
80134624/80134624             0s
0us/step
```

[76]:
```
for layer in trained_VGG19_layers.layers:
    layer.trainable=False
```

[77]:
```
VGG19_model = keras.models.Sequential([
    trained_VGG19_layers,
    Flatten(),
    Dense(256,activation='relu'),
    Dense(4,activation='softmax')
])
```

[78]:
```
VGG19_model.summary()
```

Model: "sequential_3"

Layer (type)	**Output Shape**	**Param #**
vgg19 (Functional)	(None, 7, 7, 512)	20,024,384
flatten_3 (Flatten)	(None, 25088)	0
dense_8 (Dense)	(None, 256)	6,422,784
dense_9 (Dense)	(None, 4)	1,028

Total params: 26,448,196 (100.89 MB)

Trainable params: 6,423,812 (24.50 MB)

Non-trainable params: 20,024,384 (76.39 MB)

[79]:
```
VGG19_model.compile(optimizer='Adam',loss='categorical_crossentropy',
                    metrics=['accuracy'])
```

[80]:
```
VGG19_history = VGG19_model.fit(
    VGG19_train_generator,
    epochs=20,
    validation_data = VGG19_test_generator,
    callbacks = callbacks
)
```

```
Epoch 1/20
179/179              0s 94ms/step -
accuracy: 0.6790 - loss: 1.7550
Epoch 1: val_loss did not improve from 0.07241
179/179              25s 124ms/step -
accuracy: 0.6796 - loss: 1.7494 - val_accuracy: 0.8764 - val_loss: 0.3005 -
```

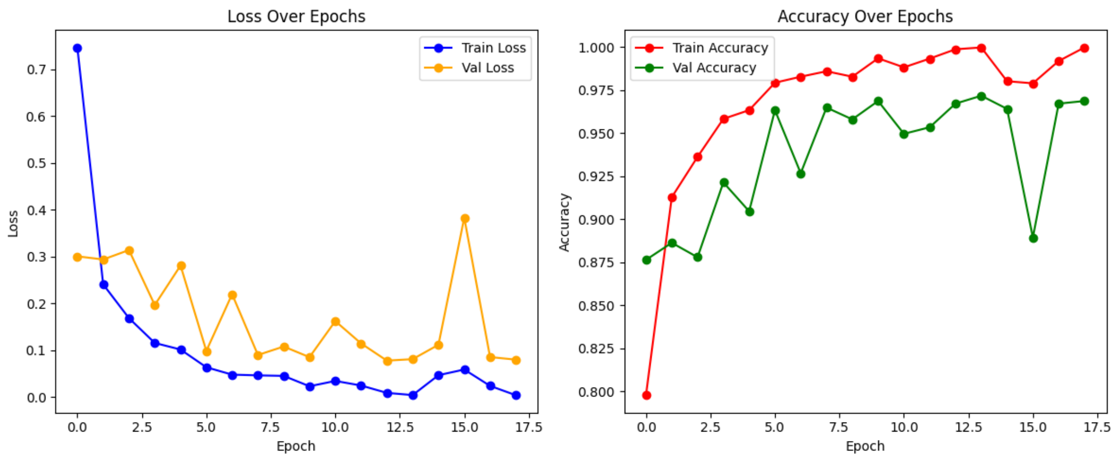
```
learning_rate: 0.0010
Epoch 2/20
179/179            0s 95ms/step -
accuracy: 0.9173 - loss: 0.2221
Epoch 2: val_loss did not improve from 0.07241
179/179            21s 116ms/step -
accuracy: 0.9172 - loss: 0.2222 - val_accuracy: 0.8863 - val_loss: 0.2938 -
learning_rate: 0.0010
Epoch 3/20
179/179            0s 90ms/step -
accuracy: 0.9237 - loss: 0.1911
Epoch 3: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9237 - loss: 0.1909 - val_accuracy: 0.8780 - val_loss: 0.3139 -
learning_rate: 0.0010
Epoch 4/20
179/179            0s 90ms/step -
accuracy: 0.9581 - loss: 0.1229
Epoch 4: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9581 - loss: 0.1229 - val_accuracy: 0.9214 - val_loss: 0.1965 -
learning_rate: 0.0010
Epoch 5/20
179/179            0s 90ms/step -
accuracy: 0.9644 - loss: 0.0989
Epoch 5: val_loss did not improve from 0.07241
179/179            20s 112ms/step -
accuracy: 0.9644 - loss: 0.0989 - val_accuracy: 0.9047 - val_loss: 0.2809 -
learning_rate: 0.0010
Epoch 6/20
179/179            0s 92ms/step -
accuracy: 0.9676 - loss: 0.0934
Epoch 6: val_loss did not improve from 0.07241
179/179            20s 113ms/step -
accuracy: 0.9677 - loss: 0.0932 - val_accuracy: 0.9634 - val_loss: 0.0984 -
learning_rate: 0.0010
Epoch 7/20
179/179            0s 91ms/step -
accuracy: 0.9856 - loss: 0.0434
Epoch 7: val_loss did not improve from 0.07241
179/179            20s 112ms/step -
accuracy: 0.9856 - loss: 0.0434 - val_accuracy: 0.9268 - val_loss: 0.2196 -
learning_rate: 0.0010
Epoch 8/20
179/179            0s 90ms/step -
accuracy: 0.9800 - loss: 0.0565
Epoch 8: val_loss did not improve from 0.07241
179/179            20s 112ms/step -
```

```
accuracy: 0.9800 - loss: 0.0564 - val_accuracy: 0.9649 - val_loss: 0.0897 -
learning_rate: 0.0010
Epoch 9/20
179/179            0s 90ms/step -
accuracy: 0.9868 - loss: 0.0395
Epoch 9: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9868 - loss: 0.0395 - val_accuracy: 0.9580 - val_loss: 0.1078 -
learning_rate: 0.0010
Epoch 10/20
179/179            0s 90ms/step -
accuracy: 0.9970 - loss: 0.0166
Epoch 10: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9970 - loss: 0.0166 - val_accuracy: 0.9687 - val_loss: 0.0851 -
learning_rate: 0.0010
Epoch 11/20
179/179            0s 90ms/step -
accuracy: 0.9969 - loss: 0.0163
Epoch 11: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9968 - loss: 0.0164 - val_accuracy: 0.9497 - val_loss: 0.1622 -
learning_rate: 0.0010
Epoch 12/20
179/179            0s 90ms/step -
accuracy: 0.9927 - loss: 0.0269
Epoch 12: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9927 - loss: 0.0268 - val_accuracy: 0.9535 - val_loss: 0.1144 -
learning_rate: 0.0010
Epoch 13/20
179/179            0s 90ms/step -
accuracy: 0.9972 - loss: 0.0142
Epoch 13: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9973 - loss: 0.0141 - val_accuracy: 0.9672 - val_loss: 0.0777 -
learning_rate: 0.0010
Epoch 14/20
179/179            0s 90ms/step -
accuracy: 0.9998 - loss: 0.0038
Epoch 14: val_loss did not improve from 0.07241
179/179            20s 111ms/step -
accuracy: 0.9998 - loss: 0.0038 - val_accuracy: 0.9718 - val_loss: 0.0809 -
learning_rate: 0.0010
Epoch 15/20
179/179            0s 91ms/step -
accuracy: 0.9839 - loss: 0.0420
Epoch 15: val_loss did not improve from 0.07241
```

```
179/179              20s 112ms/step -
accuracy: 0.9838 - loss: 0.0420 - val_accuracy: 0.9641 - val_loss: 0.1116 -
learning_rate: 0.0010
Epoch 16/20
179/179              0s 91ms/step -
accuracy: 0.9908 - loss: 0.0266
Epoch 16: val_loss did not improve from 0.07241

Epoch 16: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
179/179              20s 113ms/step -
accuracy: 0.9907 - loss: 0.0268 - val_accuracy: 0.8894 - val_loss: 0.3830 -
learning_rate: 0.0010
Epoch 17/20
179/179              0s 91ms/step -
accuracy: 0.9849 - loss: 0.0423
Epoch 17: val_loss did not improve from 0.07241
179/179              20s 112ms/step -
accuracy: 0.9849 - loss: 0.0422 - val_accuracy: 0.9672 - val_loss: 0.0854 -
learning_rate: 5.0000e-04
Epoch 18/20
179/179              0s 90ms/step -
accuracy: 0.9994 - loss: 0.0046
Epoch 18: val_loss did not improve from 0.07241
179/179              20s 110ms/step -
accuracy: 0.9994 - loss: 0.0046 - val_accuracy: 0.9687 - val_loss: 0.0798 -
learning_rate: 5.0000e-04
```

[81]:
```python
# Plotting training and validation loss and accuracy
plt.figure(figsize=(12, 5))

#  Loss
plt.subplot(1, 2, 1)
plt.plot(VGG19_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
plt.plot(VGG19_history.history['val_loss'], label='Val Loss', marker='o',␣
 ↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

#  Accuracy
plt.subplot(1, 2, 2)
plt.plot(VGG19_history.history['accuracy'], label='Train Accuracy', marker='o',␣
 ↪color='red')
plt.plot(VGG19_history.history['val_accuracy'], label='Val Accuracy',␣
 ↪marker='o', color='green')
```

```
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[83]:
```
vgg19_predictions = VGG19_model.predict(cnn_merged_generator)
```

```
63/63                7s 98ms/step
```

[85]:
```
vgg19_result = VGG19_model.evaluate(cnn_merged_generator,batch_size=BATCH_SIZE)
print('Accuracy: ',vgg19_result[1])
```

```
63/63                6s 97ms/step -
accuracy: 0.9415 - loss: 0.4506
Accuracy:  0.940500020980835
```

0.0.7 ResNet Model Building

[86]:
```
def preprocess_resnet(x):
    return x/255.0
```

[87]:
```
ResNet_train_datagen =␣
  ↪ImageDataGenerator(preprocessing_function=preprocess_resnet)
ResNet_train_generator = ResNet_train_datagen.flow_from_directory(
        train_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

Found 5712 images belonging to 4 classes.

[88]:
```
ResNet_train_generator.class_indices
```

[88]: {'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}

[89]:
```
ResNet_test_datagen = 
 ↪ImageDataGenerator(preprocessing_function=preprocess_resnet)
ResNet_test_generator = ResNet_test_datagen.flow_from_directory(
        test_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

Found 1311 images belonging to 4 classes.

[90]:
```
ResNet_test_generator.class_indices
```

[90]: {'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}

[91]:
```
trained_ResNet_layers = 
 ↪ResNet50V2(weights='imagenet',include_top=False,input_shape=(IMAGE_SIZE,IMAGE_SIZE,3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-
applications/resnet/resnet50v2_weights_tf_dim_ordering_tf_kernels_notop.h5
94668760/94668760            0s
0us/step
```

[92]:
```
for layer in trained_ResNet_layers.layers:
    layer.trainable = False
```

[93]:
```
ResNet_model = keras.models.Sequential([
    trained_ResNet_layers,
    keras.layers.GlobalAveragePooling2D(),
    Dense(256, activation='relu'),
    Dense(4, activation='softmax')
])
```

[94]:
```
ResNet_model.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
resnet50v2 (Functional)	(None, 7, 7, 2048)	23,564,800
global_average_pooling2d (GlobalAveragePooling2D)	(None, 2048)	0

```
 dense_10 (Dense)                  (None, 256)                   524,544

 dense_11 (Dense)                  (None, 4)                       1,028
```

```
 Total params: 24,090,372 (91.90 MB)

 Trainable params: 525,572 (2.00 MB)

 Non-trainable params: 23,564,800 (89.89 MB)
```

[95]:
```python
ResNet_model.compile(optimizer='Adam',
              loss='categorical_crossentropy',
               metrics=['accuracy']
                    )
```

[96]:
```python
ResNet_history = ResNet_model.fit(
        ResNet_train_generator,
        epochs = 20,
        validation_data = ResNet_test_generator,
        callbacks = callbacks
        )
```

```
Epoch 1/20
179/179                   0s 101ms/step -
accuracy: 0.7482 - loss: 0.7112
Epoch 1: val_loss did not improve from 0.07241
179/179                   44s 167ms/step -
accuracy: 0.7487 - loss: 0.7098 - val_accuracy: 0.9077 - val_loss: 0.2662 -
learning_rate: 0.0010
Epoch 2/20
179/179                   0s 79ms/step -
accuracy: 0.9316 - loss: 0.1978
Epoch 2: val_loss did not improve from 0.07241
179/179                   17s 97ms/step -
accuracy: 0.9316 - loss: 0.1977 - val_accuracy: 0.9138 - val_loss: 0.2471 -
learning_rate: 0.0010
Epoch 3/20
179/179                   0s 82ms/step -
accuracy: 0.9506 - loss: 0.1319
Epoch 3: val_loss did not improve from 0.07241
179/179                   18s 101ms/step -
accuracy: 0.9506 - loss: 0.1319 - val_accuracy: 0.9314 - val_loss: 0.1782 -
learning_rate: 0.0010
Epoch 4/20
```

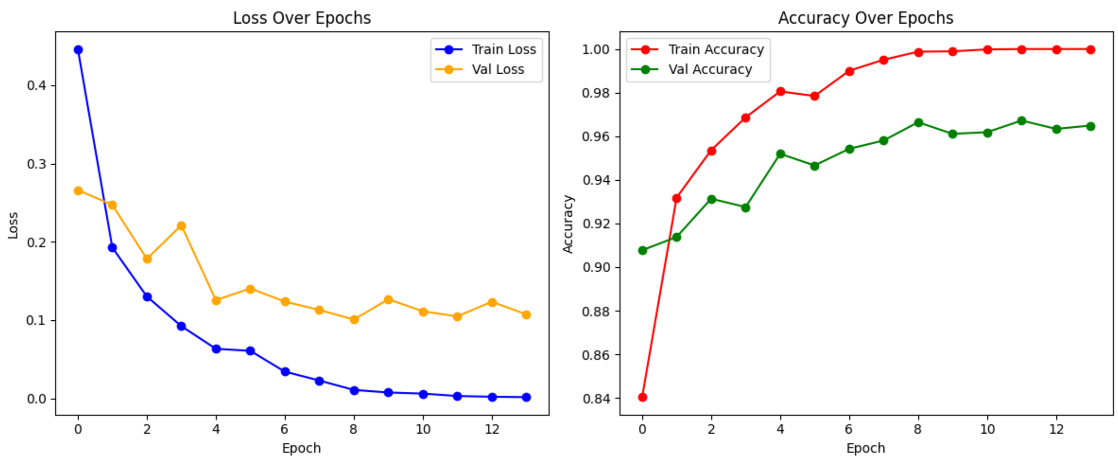
```
179/179            0s 80ms/step -
accuracy: 0.9735 - loss: 0.0833
Epoch 4: val_loss did not improve from 0.07241
179/179            18s 99ms/step -
accuracy: 0.9735 - loss: 0.0834 - val_accuracy: 0.9275 - val_loss: 0.2211 -
learning_rate: 0.0010
Epoch 5/20
179/179            0s 84ms/step -
accuracy: 0.9826 - loss: 0.0596
Epoch 5: val_loss did not improve from 0.07241
179/179            19s 104ms/step -
accuracy: 0.9826 - loss: 0.0596 - val_accuracy: 0.9519 - val_loss: 0.1255 -
learning_rate: 0.0010
Epoch 6/20
179/179            0s 83ms/step -
accuracy: 0.9847 - loss: 0.0502
Epoch 6: val_loss did not improve from 0.07241
179/179            19s 103ms/step -
accuracy: 0.9847 - loss: 0.0502 - val_accuracy: 0.9466 - val_loss: 0.1404 -
learning_rate: 0.0010
Epoch 7/20
179/179            0s 81ms/step -
accuracy: 0.9904 - loss: 0.0350
Epoch 7: val_loss did not improve from 0.07241
179/179            18s 99ms/step -
accuracy: 0.9904 - loss: 0.0350 - val_accuracy: 0.9542 - val_loss: 0.1236 -
learning_rate: 0.0010
Epoch 8/20
179/179            0s 83ms/step -
accuracy: 0.9949 - loss: 0.0277
Epoch 8: val_loss did not improve from 0.07241
179/179            18s 102ms/step -
accuracy: 0.9949 - loss: 0.0277 - val_accuracy: 0.9580 - val_loss: 0.1129 -
learning_rate: 0.0010
Epoch 9/20
179/179            0s 80ms/step -
accuracy: 0.9995 - loss: 0.0091
Epoch 9: val_loss did not improve from 0.07241
179/179            18s 99ms/step -
accuracy: 0.9995 - loss: 0.0091 - val_accuracy: 0.9664 - val_loss: 0.1006 -
learning_rate: 0.0010
Epoch 10/20
179/179            0s 80ms/step -
accuracy: 0.9998 - loss: 0.0068
Epoch 10: val_loss did not improve from 0.07241
179/179            18s 99ms/step -
accuracy: 0.9998 - loss: 0.0068 - val_accuracy: 0.9611 - val_loss: 0.1266 -
learning_rate: 0.0010
```

```
Epoch 11/20
179/179              0s 80ms/step -
accuracy: 0.9994 - loss: 0.0080
Epoch 11: val_loss did not improve from 0.07241
179/179              18s 98ms/step -
accuracy: 0.9994 - loss: 0.0080 - val_accuracy: 0.9619 - val_loss: 0.1113 -
learning_rate: 0.0010
Epoch 12/20
179/179              0s 84ms/step -
accuracy: 1.0000 - loss: 0.0029
Epoch 12: val_loss did not improve from 0.07241

Epoch 12: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
179/179              18s 102ms/step -
accuracy: 1.0000 - loss: 0.0029 - val_accuracy: 0.9672 - val_loss: 0.1047 -
learning_rate: 0.0010
Epoch 13/20
179/179              0s 78ms/step -
accuracy: 1.0000 - loss: 0.0023
Epoch 13: val_loss did not improve from 0.07241
179/179              17s 97ms/step -
accuracy: 1.0000 - loss: 0.0023 - val_accuracy: 0.9634 - val_loss: 0.1234 -
learning_rate: 5.0000e-04
Epoch 14/20
179/179              0s 84ms/step -
accuracy: 1.0000 - loss: 0.0015
Epoch 14: val_loss did not improve from 0.07241
179/179              18s 102ms/step -
accuracy: 1.0000 - loss: 0.0015 - val_accuracy: 0.9649 - val_loss: 0.1073 -
learning_rate: 5.0000e-04
```

[98]:

```
#Plotting training and validation loss and accuracy
plt.figure(figsize=(12, 5))

#  Loss
plt.subplot(1, 2, 1)
plt.plot(ResNet_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
plt.plot(ResNet_history.history['val_loss'], label='Val Loss', marker='o',␣
 ↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

#  Accuracy
plt.subplot(1, 2, 2)
```

```
plt.plot(ResNet_history.history['accuracy'], label='Train Accuracy',␣
  ↪marker='o', color='red')
plt.plot(ResNet_history.history['val_accuracy'], label='Val Accuracy',␣
  ↪marker='o', color='green')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[99]:
```
resnet_predictions = ResNet_model.predict(cnn_merged_generator)
```

```
63/63                 12s 123ms/step
```

[101]:
```
resnet_result = ResNet_model.evaluate(cnn_merged_generator,␣
  ↪batch_size=BATCH_SIZE)
print('Accuracy: ',resnet_result[1])
```

```
63/63                 4s 63ms/step -
accuracy: 0.9758 - loss: 0.1975
Accuracy:  0.9695000052452087
```

0.0.8 MobileNet Model Building

[102]:
```
def preprocess_mobilenet(x):
    return x/255.0
```

[103]:
```
MobileNet_train_datagen =␣
  ↪ImageDataGenerator(preprocessing_function=preprocess_mobilenet)
MobileNet_train_generator = MobileNet_train_datagen.flow_from_directory(
```

```
        train_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

Found 5712 images belonging to 4 classes.

[104]:
```
MobileNet_train_generator.class_indices
```

[104]: {'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}

[105]:
```
MobileNet_test_datagen =␣
 ↪ImageDataGenerator(preprocessing_function=preprocess_mobilenet)
MobileNet_test_generator = MobileNet_test_datagen.flow_from_directory(
        test_path,
        target_size=(IMAGE_SIZE,IMAGE_SIZE),
        batch_size=BATCH_SIZE,
        class_mode='categorical')
```

Found 1311 images belonging to 4 classes.

[106]:
```
MobileNet_test_generator.class_indices
```

[106]: {'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}

[107]:
```
trained_MobileNet_layers =␣
 ↪MobileNetV2(weights='imagenet',include_top=False,input_shape=(IMAGE_SIZE,IMAGE_SIZE,3))
```

```
Downloading data from https://storage.googleapis.com/tensorflow/keras-applicatio
ns/mobilenet_v2/mobilenet_v2_weights_tf_dim_ordering_tf_kernels_1.0_224_no_top.h
5
9406464/9406464             0s
0us/step
```

[108]:
```
for layer in trained_MobileNet_layers.layers:
    layer.trainable = False
```

[109]:
```
MobileNet_model = keras.models.Sequential([
    trained_MobileNet_layers,
    keras.layers.GlobalAveragePooling2D(),
    Dense(256, activation='relu'),
    Dense(4, activation='softmax')
])
```

[110]:
```
MobileNet_model.summary()
```

Model: "sequential_5"

```
 Layer (type)                    Output Shape                  Param #

 mobilenetv2_1.00_224            (None, 7, 7, 1280)          2,257,984
 (Functional)

 global_average_pooling2d_1      (None, 1280)                        0
 (GlobalAveragePooling2D)

 dense_12 (Dense)                (None, 256)                   327,936

 dense_13 (Dense)                (None, 4)                       1,028
```

```
Total params: 2,586,948 (9.87 MB)

Trainable params: 328,964 (1.25 MB)

Non-trainable params: 2,257,984 (8.61 MB)
```

[111]:

```python
MobileNet_model.compile(optimizer='Adam',
              loss='categorical_crossentropy',
               metrics=['accuracy']
)
```

[112]:

```python
MobileNet_history = MobileNet_model.fit(
        MobileNet_train_generator,
        epochs = 20,
        validation_data = MobileNet_test_generator,
        callbacks = callbacks
        )
```

```
Epoch 1/20
179/179              0s 95ms/step -
accuracy: 0.7928 - loss: 0.5370
Epoch 1: val_loss did not improve from 0.07241
179/179              38s 151ms/step -
accuracy: 0.7932 - loss: 0.5362 - val_accuracy: 0.8741 - val_loss: 0.3568 -
learning_rate: 0.0010
Epoch 2/20
179/179              0s 81ms/step -
accuracy: 0.9105 - loss: 0.2414
Epoch 2: val_loss did not improve from 0.07241
179/179              18s 100ms/step -
accuracy: 0.9106 - loss: 0.2412 - val_accuracy: 0.9275 - val_loss: 0.2011 -
learning_rate: 0.0010
```

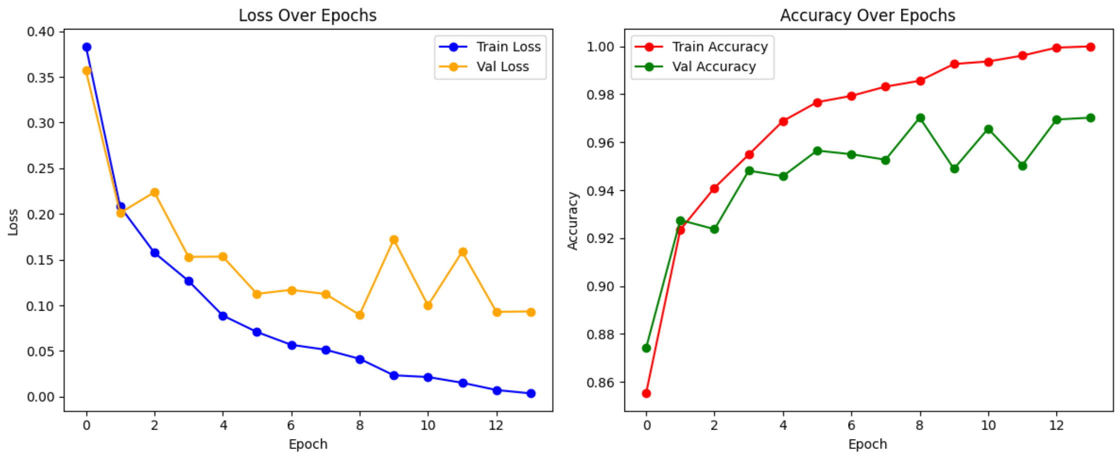
```
Epoch 3/20
179/179            0s 81ms/step -
accuracy: 0.9433 - loss: 0.1550
Epoch 3: val_loss did not improve from 0.07241
179/179            18s 99ms/step -
accuracy: 0.9433 - loss: 0.1550 - val_accuracy: 0.9237 - val_loss: 0.2238 -
learning_rate: 0.0010
Epoch 4/20
179/179            0s 77ms/step -
accuracy: 0.9484 - loss: 0.1484
Epoch 4: val_loss did not improve from 0.07241
179/179            17s 95ms/step -
accuracy: 0.9484 - loss: 0.1482 - val_accuracy: 0.9481 - val_loss: 0.1530 -
learning_rate: 0.0010
Epoch 5/20
179/179            0s 79ms/step -
accuracy: 0.9711 - loss: 0.0837
Epoch 5: val_loss did not improve from 0.07241
179/179            17s 97ms/step -
accuracy: 0.9711 - loss: 0.0837 - val_accuracy: 0.9458 - val_loss: 0.1534 -
learning_rate: 0.0010
Epoch 6/20
179/179            0s 91ms/step -
accuracy: 0.9781 - loss: 0.0708
Epoch 6: val_loss did not improve from 0.07241
179/179            20s 110ms/step -
accuracy: 0.9781 - loss: 0.0708 - val_accuracy: 0.9565 - val_loss: 0.1126 -
learning_rate: 0.0010
Epoch 7/20
179/179            0s 78ms/step -
accuracy: 0.9830 - loss: 0.0511
Epoch 7: val_loss did not improve from 0.07241
179/179            17s 96ms/step -
accuracy: 0.9830 - loss: 0.0512 - val_accuracy: 0.9550 - val_loss: 0.1169 -
learning_rate: 0.0010
Epoch 8/20
179/179            0s 84ms/step -
accuracy: 0.9884 - loss: 0.0410
Epoch 8: val_loss did not improve from 0.07241
179/179            19s 103ms/step -
accuracy: 0.9883 - loss: 0.0411 - val_accuracy: 0.9527 - val_loss: 0.1125 -
learning_rate: 0.0010
Epoch 9/20
179/179            0s 89ms/step -
accuracy: 0.9879 - loss: 0.0372
Epoch 9: val_loss did not improve from 0.07241
179/179            20s 110ms/step -
accuracy: 0.9879 - loss: 0.0372 - val_accuracy: 0.9703 - val_loss: 0.0897 -
```

```
learning_rate: 0.0010
Epoch 10/20
179/179              0s 80ms/step -
accuracy: 0.9964 - loss: 0.0193
Epoch 10: val_loss did not improve from 0.07241
179/179              17s 97ms/step -
accuracy: 0.9964 - loss: 0.0194 - val_accuracy: 0.9489 - val_loss: 0.1720 -
learning_rate: 0.0010
Epoch 11/20
179/179              0s 76ms/step -
accuracy: 0.9915 - loss: 0.0254
Epoch 11: val_loss did not improve from 0.07241
179/179              17s 94ms/step -
accuracy: 0.9915 - loss: 0.0254 - val_accuracy: 0.9657 - val_loss: 0.0999 -
learning_rate: 0.0010
Epoch 12/20
179/179              0s 77ms/step -
accuracy: 0.9959 - loss: 0.0168
Epoch 12: val_loss did not improve from 0.07241

Epoch 12: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
179/179              17s 94ms/step -
accuracy: 0.9959 - loss: 0.0168 - val_accuracy: 0.9504 - val_loss: 0.1587 -
learning_rate: 0.0010
Epoch 13/20
179/179              0s 82ms/step -
accuracy: 0.9992 - loss: 0.0109
Epoch 13: val_loss did not improve from 0.07241
179/179              18s 101ms/step -
accuracy: 0.9992 - loss: 0.0109 - val_accuracy: 0.9695 - val_loss: 0.0929 -
learning_rate: 5.0000e-04
Epoch 14/20
179/179              0s 76ms/step -
accuracy: 1.0000 - loss: 0.0039
Epoch 14: val_loss did not improve from 0.07241
179/179              17s 93ms/step -
accuracy: 1.0000 - loss: 0.0039 - val_accuracy: 0.9703 - val_loss: 0.0933 -
learning_rate: 5.0000e-04
```

[113]:

```python
# Plotting training and validation loss and accuracy
plt.figure(figsize=(12, 5))

#  Loss
plt.subplot(1, 2, 1)
plt.plot(MobileNet_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
```

```
plt.plot(MobileNet_history.history['val_loss'], label='Val Loss', marker='o',␣
↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

#  Accuracy
plt.subplot(1, 2, 2)
plt.plot(MobileNet_history.history['accuracy'], label='Train Accuracy',␣
↪marker='o', color='red')
plt.plot(MobileNet_history.history['val_accuracy'], label='Val Accuracy',␣
↪marker='o', color='green')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[114]:
```
mobilenet_predictions = MobileNet_model.predict(cnn_merged_generator)
```

```
63/63                  12s 120ms/step
```

[115]:
```
mobilenet_result = MobileNet_model.evaluate(cnn_merged_generator,␣
↪batch_size=BATCH_SIZE)
print('Accuracy: ',mobilenet_result[1])
```

```
63/63                  6s 88ms/step -
accuracy: 0.9667 - loss: 0.3193
Accuracy:  0.9639999866485596
```

0.0.9 EfficientNet Model Building

[116]:
```
def preprocess_mobilenet(x):
    return x/255.0
```

[117]:
```
EffNetB3_train_datagen =␣
↪ImageDataGenerator(preprocessing_function=efficientnet_preprocess)
EffNetB3_test_datagen =␣
↪ImageDataGenerator(preprocessing_function=efficientnet_preprocess)
```

[170]:
```
EffNetB3_train_generator = EffNetB3_train_datagen.flow_from_directory(
    train_path,
    target_size=(300,300),
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 5712 images belonging to 4 classes.
```

[171]:
```
EffNetB3_train_generator.class_indices
```

[171]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[172]:
```
EffNetB3_test_generator = EffNetB3_test_datagen.flow_from_directory(
    test_path,
    target_size=(300,300),
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)
```

```
Found 1311 images belonging to 4 classes.
```

[173]:
```
EffNetB3_test_generator.class_indices
```

[173]:
```
{'glioma': 0, 'meningioma': 1, 'notumor': 2, 'pituitary': 3}
```

[174]:
```
base_effnetb3 = EfficientNetB3(
    weights='imagenet',
    include_top=False,
    input_shape=(300, 300, 3)
)
```

[175]:
```
for layer in base_effnetb3.layers:
    layer.trainable = False
```

[176]:
```
EffNetB3_model = keras.models.Sequential([
    base_effnetb3,
    layers.GlobalAveragePooling2D(),
    layers.Dense(256, activation='relu'),
```

```
    layers.Dense(4, activation='softmax')
])
```

[177]:
```
EffNetB3_model.summary()
```

Model: "sequential_10"

Layer (type)	Output Shape	Param #
efficientnetb3 (Functional)	(None, 10, 10, 1536)	10,783,535
global_average_pooling2d_6 (GlobalAveragePooling2D)	(None, 1536)	0
dense_22 (Dense)	(None, 256)	393,472
dense_23 (Dense)	(None, 4)	1,028

Total params: 11,178,035 (42.64 MB)

Trainable params: 394,500 (1.50 MB)

Non-trainable params: 10,783,535 (41.14 MB)

[178]:
```
EffNetB3_model.compile(
    optimizer=Adam(),
    loss='categorical_crossentropy',
    metrics=['accuracy']
)
```

[184]:
```
EffNetB3_history = EffNetB3_model.fit(
    EffNetB3_train_generator,
    epochs=20,
    validation_data=EffNetB3_test_generator,
    callbacks=callbacks
)
```

```
Epoch 1/20
179/179              0s 117ms/step -
accuracy: 0.9682 - loss: 0.0881
Epoch 1: val_loss did not improve from 0.04584
179/179              26s 145ms/step -
accuracy: 0.9682 - loss: 0.0881 - val_accuracy: 0.9664 - val_loss: 0.0964 -
```

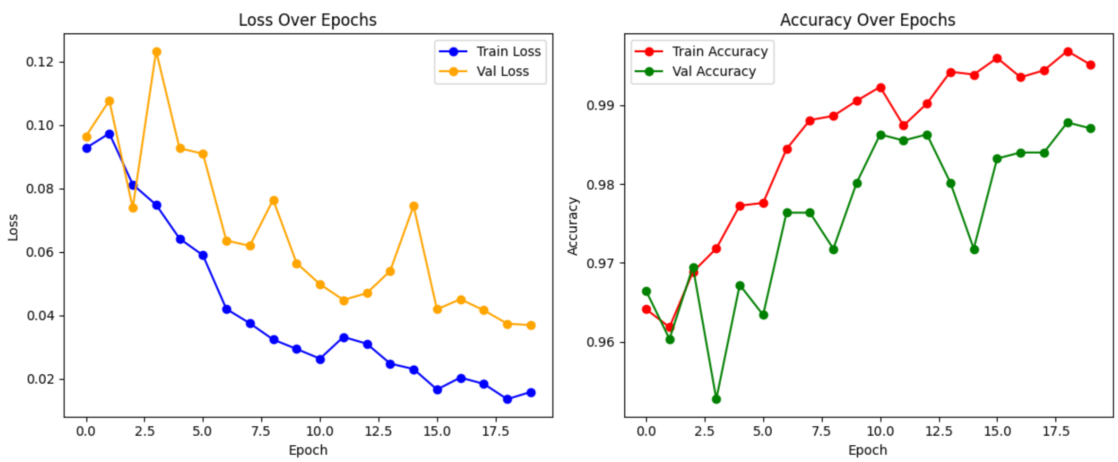
```
learning_rate: 0.0010
Epoch 2/20
179/179             0s 131ms/step -
accuracy: 0.9635 - loss: 0.0964
Epoch 2: val_loss did not improve from 0.04584
179/179             28s 158ms/step -
accuracy: 0.9635 - loss: 0.0964 - val_accuracy: 0.9603 - val_loss: 0.1077 -
learning_rate: 0.0010
Epoch 3/20
179/179             0s 127ms/step -
accuracy: 0.9704 - loss: 0.0815
Epoch 3: val_loss did not improve from 0.04584
179/179             29s 160ms/step -
accuracy: 0.9704 - loss: 0.0815 - val_accuracy: 0.9695 - val_loss: 0.0738 -
learning_rate: 0.0010
Epoch 4/20
179/179             0s 118ms/step -
accuracy: 0.9720 - loss: 0.0759
Epoch 4: val_loss did not improve from 0.04584
179/179             26s 147ms/step -
accuracy: 0.9720 - loss: 0.0759 - val_accuracy: 0.9527 - val_loss: 0.1233 -
learning_rate: 0.0010
Epoch 5/20
179/179             0s 148ms/step -
accuracy: 0.9792 - loss: 0.0658
Epoch 5: val_loss did not improve from 0.04584
179/179             32s 180ms/step -
accuracy: 0.9791 - loss: 0.0658 - val_accuracy: 0.9672 - val_loss: 0.0926 -
learning_rate: 0.0010
Epoch 6/20
179/179             0s 124ms/step -
accuracy: 0.9799 - loss: 0.0547
Epoch 6: val_loss did not improve from 0.04584

Epoch 6: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
179/179             28s 155ms/step -
accuracy: 0.9799 - loss: 0.0547 - val_accuracy: 0.9634 - val_loss: 0.0909 -
learning_rate: 0.0010
Epoch 7/20
179/179             0s 136ms/step -
accuracy: 0.9839 - loss: 0.0414
Epoch 7: val_loss did not improve from 0.04584
179/179             29s 164ms/step -
accuracy: 0.9839 - loss: 0.0414 - val_accuracy: 0.9764 - val_loss: 0.0635 -
learning_rate: 5.0000e-04
Epoch 8/20
179/179             0s 122ms/step -
accuracy: 0.9862 - loss: 0.0380
```

```
Epoch 8: val_loss did not improve from 0.04584
179/179              28s 154ms/step -
accuracy: 0.9862 - loss: 0.0380 - val_accuracy: 0.9764 - val_loss: 0.0618 -
learning_rate: 5.0000e-04
Epoch 9/20
179/179              0s 123ms/step -
accuracy: 0.9902 - loss: 0.0301
Epoch 9: val_loss did not improve from 0.04584
179/179              26s 144ms/step -
accuracy: 0.9902 - loss: 0.0301 - val_accuracy: 0.9718 - val_loss: 0.0764 -
learning_rate: 5.0000e-04
Epoch 10/20
179/179              0s 137ms/step -
accuracy: 0.9866 - loss: 0.0346
Epoch 10: val_loss did not improve from 0.04584
179/179              30s 165ms/step -
accuracy: 0.9866 - loss: 0.0346 - val_accuracy: 0.9802 - val_loss: 0.0564 -
learning_rate: 5.0000e-04
Epoch 11/20
179/179              0s 121ms/step -
accuracy: 0.9926 - loss: 0.0252
Epoch 11: val_loss did not improve from 0.04584
179/179              27s 151ms/step -
accuracy: 0.9926 - loss: 0.0253 - val_accuracy: 0.9863 - val_loss: 0.0497 -
learning_rate: 5.0000e-04
Epoch 12/20
179/179              0s 122ms/step -
accuracy: 0.9887 - loss: 0.0296
Epoch 12: val_loss improved from 0.04584 to 0.04480, saving model to CCN.h5
179/179              28s 155ms/step -
accuracy: 0.9887 - loss: 0.0297 - val_accuracy: 0.9855 - val_loss: 0.0448 -
learning_rate: 5.0000e-04
Epoch 13/20
179/179              0s 139ms/step -
accuracy: 0.9893 - loss: 0.0357
Epoch 13: val_loss did not improve from 0.04480
179/179              30s 169ms/step -
accuracy: 0.9893 - loss: 0.0357 - val_accuracy: 0.9863 - val_loss: 0.0469 -
learning_rate: 5.0000e-04
Epoch 14/20
179/179              0s 123ms/step -
accuracy: 0.9940 - loss: 0.0240
Epoch 14: val_loss did not improve from 0.04480
179/179              28s 157ms/step -
accuracy: 0.9940 - loss: 0.0240 - val_accuracy: 0.9802 - val_loss: 0.0539 -
learning_rate: 5.0000e-04
Epoch 15/20
179/179              0s 138ms/step -
```

```
accuracy: 0.9931 - loss: 0.0227
Epoch 15: val_loss did not improve from 0.04480

Epoch 15: ReduceLROnPlateau reducing learning rate to 0.0002500000118743628.
179/179              30s 167ms/step -
accuracy: 0.9931 - loss: 0.0228 - val_accuracy: 0.9718 - val_loss: 0.0744 -
learning_rate: 5.0000e-04
Epoch 16/20
179/179              0s 102ms/step -
accuracy: 0.9952 - loss: 0.0181
Epoch 16: val_loss improved from 0.04480 to 0.04185, saving model to CCN.h5
179/179              24s 134ms/step -
accuracy: 0.9952 - loss: 0.0181 - val_accuracy: 0.9832 - val_loss: 0.0418 -
learning_rate: 2.5000e-04
Epoch 17/20
179/179              0s 127ms/step -
accuracy: 0.9924 - loss: 0.0214
Epoch 17: val_loss did not improve from 0.04185
179/179              27s 150ms/step -
accuracy: 0.9924 - loss: 0.0214 - val_accuracy: 0.9840 - val_loss: 0.0450 -
learning_rate: 2.5000e-04
Epoch 18/20
179/179              0s 125ms/step -
accuracy: 0.9959 - loss: 0.0177
Epoch 18: val_loss improved from 0.04185 to 0.04155, saving model to CCN.h5
179/179              28s 156ms/step -
accuracy: 0.9959 - loss: 0.0177 - val_accuracy: 0.9840 - val_loss: 0.0416 -
learning_rate: 2.5000e-04
Epoch 19/20
179/179              0s 123ms/step -
accuracy: 0.9976 - loss: 0.0121
Epoch 19: val_loss improved from 0.04155 to 0.03730, saving model to CCN.h5
179/179              28s 156ms/step -
accuracy: 0.9975 - loss: 0.0121 - val_accuracy: 0.9878 - val_loss: 0.0373 -
learning_rate: 2.5000e-04
Epoch 20/20
179/179              0s 116ms/step -
accuracy: 0.9957 - loss: 0.0162
Epoch 20: val_loss improved from 0.03730 to 0.03687, saving model to CCN.h5
179/179              27s 149ms/step -
accuracy: 0.9957 - loss: 0.0162 - val_accuracy: 0.9870 - val_loss: 0.0369 -
learning_rate: 2.5000e-04
```

[188]:
```
plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
```

```
plt.plot(EffNetB3_history.history['loss'], label='Train Loss', marker='o',␣
 ↪color='blue')
plt.plot(EffNetB3_history.history['val_loss'], label='Val Loss', marker='o',␣
 ↪color='orange')
plt.title('Loss Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(EffNetB3_history.history['accuracy'], label='Train Accuracy',␣
 ↪marker='o', color='red')
plt.plot(EffNetB3_history.history['val_accuracy'], label='Val Accuracy',␣
 ↪marker='o', color='green')
plt.title('Accuracy Over Epochs')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()

plt.tight_layout()
plt.show()
```



[189]:
```
cnn_merged_datagen =␣
 ↪ImageDataGenerator(preprocessing_function=efficientnet_preprocess)
cnn_merged_generator = cnn_merged_datagen.flow_from_directory(
    output_path,
    target_size=(300, 300),  # Important for EfficientNetB3
    batch_size=BATCH_SIZE,
    class_mode='categorical'
)
```

```
effnetb3_predictions = EffNetB3_model.predict(cnn_merged_generator)
```

```
Found 2000 images belonging to 4 classes.
63/63                7s 107ms/step
```

[190]:
```
effnetb3_result = EffNetB3_model.evaluate(cnn_merged_generator,␣
↪batch_size=BATCH_SIZE)
print('Accuracy:', effnetb3_result[1])
```

```
63/63                6s 94ms/step -
accuracy: 0.9699 - loss: 0.2527
Accuracy: 0.9700000286102295
```

0.0.10 Compare Between Models

[193]:
```
models = ['Best CNN', 'Best MobileNetV2', 'Best VGG16', 'Best VGG19', 'Best␣
↪ResNest50', 'Best EfficientNetB3']

best_train_accuracy = [
    cnn_history.history['accuracy'][np.argmax(cnn_history.
↪history['val_accuracy'])],
    MobileNet_history.history['accuracy'][np.argmax(MobileNet_history.
↪history['val_accuracy'])],
    VGG16_history.history['accuracy'][np.argmax(VGG16_history.
↪history['val_accuracy'])],
    VGG19_history.history['accuracy'][np.argmax(VGG19_history.
↪history['val_accuracy'])],
    ResNet_history.history['accuracy'][np.argmax(ResNet_history.
↪history['val_accuracy'])],
    EffNetB3_history.history['accuracy'][np.argmax(EffNetB3_history.
↪history['val_accuracy'])]
]

best_val_accuracy = [
    cnn_history.history['val_accuracy'][np.argmax(cnn_history.
↪history['val_accuracy'])],
    MobileNet_history.history['val_accuracy'][np.argmax(MobileNet_history.
↪history['val_accuracy'])],
    VGG16_history.history['val_accuracy'][np.argmax(VGG16_history.
↪history['val_accuracy'])],
    VGG19_history.history['val_accuracy'][np.argmax(VGG19_history.
↪history['val_accuracy'])],
    ResNet_history.history['val_accuracy'][np.argmax(ResNet_history.
↪history['val_accuracy'])],
    EffNetB3_history.history['val_accuracy'][np.argmax(EffNetB3_history.
↪history['val_accuracy'])]
```

```
]
```

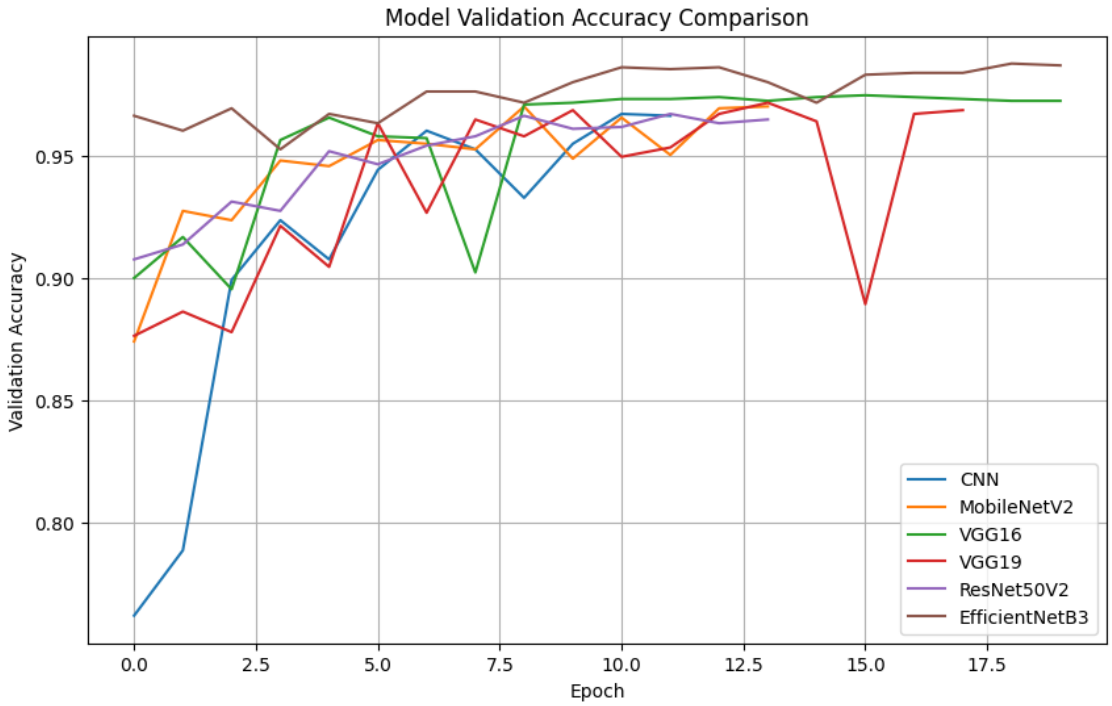
[195]:

```
history = {
    "CNN": {
        "accuracy": cnn_history.history['accuracy'],
        "val_accuracy": cnn_history.history['val_accuracy'],
        "loss": cnn_history.history['loss'],
        "val_loss": cnn_history.history['val_loss']
    },
    "MobileNetV2": {
        "accuracy": MobileNet_history.history['accuracy'],
        "val_accuracy": MobileNet_history.history['val_accuracy'],
        "loss": MobileNet_history.history['loss'],
        "val_loss": MobileNet_history.history['val_loss']
    },
    "VGG16": {
        "accuracy": VGG16_history.history['accuracy'],
        "val_accuracy": VGG16_history.history['val_accuracy'],
        "loss": VGG16_history.history['loss'],
        "val_loss": VGG16_history.history['val_loss']
    },
    "VGG19": {
        "accuracy": VGG19_history.history['accuracy'],
        "val_accuracy": VGG19_history.history['val_accuracy'],
        "loss": VGG19_history.history['loss'],
        "val_loss": VGG19_history.history['val_loss']
    },
    "ResNet50V2": {
        "accuracy": ResNet_history.history['accuracy'],
        "val_accuracy": ResNet_history.history['val_accuracy'],
        "loss": ResNet_history.history['loss'],
        "val_loss": ResNet_history.history['val_loss']
    },
    "EfficientNetB3": {
        "accuracy": EffNetB3_history.history['accuracy'],
        "val_accuracy": EffNetB3_history.history['val_accuracy'],
        "loss": EffNetB3_history.history['loss'],
        "val_loss": EffNetB3_history.history['val_loss']
    }
}
```

[196]:

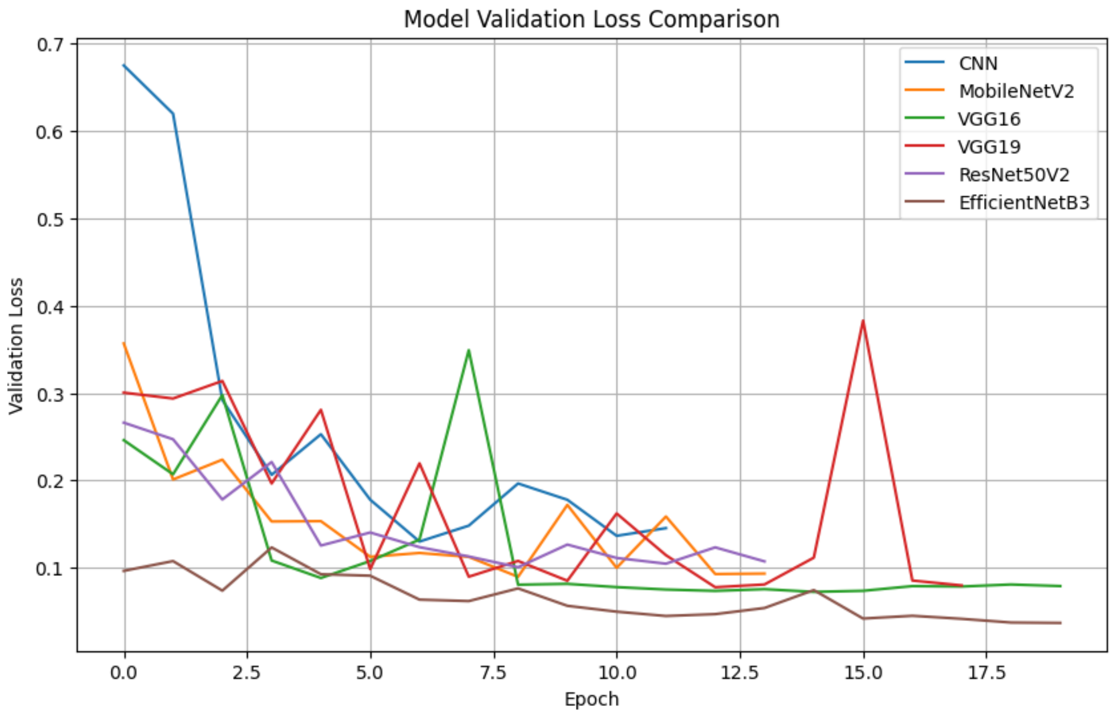
```
plt.figure(figsize=(10, 6))
for model, values in history.items():
    plt.plot(values['val_accuracy'], label=model)
plt.title('Model Validation Accuracy Comparison')
plt.ylabel('Validation Accuracy')
plt.xlabel('Epoch')
```

```
plt.legend()
plt.grid(True)
plt.show()
```



[197]:

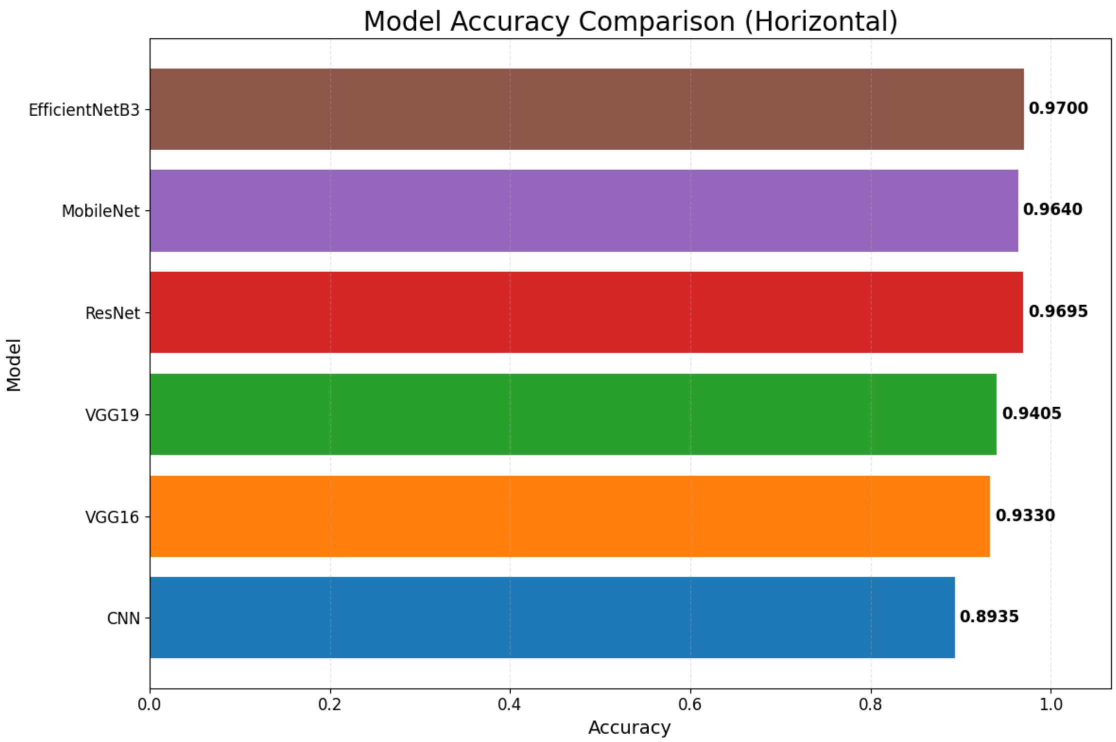
```
plt.figure(figsize=(10, 6))
for model, values in history.items():
    plt.plot(values['val_loss'], label=model)
plt.title('Model Validation Loss Comparison')
plt.ylabel('Validation Loss')
plt.xlabel('Epoch')
plt.legend()
plt.grid(True)
plt.show()
```



[198]:
```
THE_ALL_RESULTS = {
    'CNN': cnn_result[1],
    'VGG16': vgg16_result[1],
    'VGG19': vgg19_result[1],
    'ResNet': resnet_result[1],
    'MobileNet': mobilenet_result[1],
    'EfficientNetB3': effnetb3_result[1]
}
history = {
    'CNN': cnn_history.history,
    'MobileNetV2': MobileNet_history.history,
    'VGG16': VGG16_history.history,
    'VGG19': VGG19_history.history,
    'ResNet': ResNet_history.history,
    'EfficientNetB3': EffNetB3_history.history
}
print("\nModels ranked by accuracy:")
sorted_results = sorted(THE_ALL_RESULTS.items(), key=lambda x: x[1],␣
 ↪reverse=True)
for i, (model, accuracy) in enumerate(sorted_results, 1):
    print(f"{i}. {model}: {accuracy:.4f}")

plt.figure(figsize=(12, 8))
```

```python
models = list(THE_ALL_RESULTS.keys())
accuracies = list(THE_ALL_RESULTS.values())

bars = plt.barh(models, accuracies, color = ['#1f77b4', '#ff7f0e', '#2ca02c',␣
↪'#d62728', '#9467bd', '#8c564b'])

# Add value labels at the end of each bar
for bar, accuracy in zip(bars, accuracies):
    plt.text(bar.get_width() + 0.005, bar.get_y() + bar.get_height()/2,
             f'{accuracy:.4f}', ha='left', va='center', fontsize=12,␣
↪fontweight='bold')

plt.title('Model Accuracy Comparison (Horizontal)', fontsize=20)
plt.xlabel('Accuracy', fontsize=14)
plt.ylabel('Model', fontsize=14)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)

# Add grid for better readability
plt.grid(axis='x', alpha=0.3, linestyle='--')

# Set x-axis limits to better show differences
plt.xlim(0, max(THE_ALL_RESULTS.values()) * 1.1)

plt.tight_layout()
plt.show()
```

```
Models ranked by accuracy:
1. EfficientNetB3: 0.9700
2. ResNet: 0.9695
3. MobileNet: 0.9640
4. VGG19: 0.9405
5. VGG16: 0.9330
6. CNN: 0.8935
```


Model Accuracy Comparison (Horizontal)
EfficientNetB3
MobileNet
ResNet
VGG19
VGG16
CNN
0.9700
0.9640
0.9695
0.9405
0.9330
0.8935
Model
0.0
0.2
0.4
0.6
0.8
1.0
Accuracy

```
[ ]:
```