# Brain Tumor MRI Classification

This project demonstrates the classification of brain tumors using MRI images with deep learning techniques, based on the **"Brain Tumor MRI Dataset."**

**Kaggle Dataset:** Brain Tumor MRI Dataset

**GitHub Repository:** Brain Tumor MRI Classification Project

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**Note:** You can run the project on both a local device and Google Colab, or jump directly to the `streamlit run` command to get started with the application right away.

# 1. Kaggle Installation

```
# Install the Kaggle library
!pip install kaggle --quiet

# Create a directory for the Kaggle API token
!mkdir -p ~/.kaggle

# Upload your kaggle.json file
# (You need to download this from your Kaggle account: My Account >
API > Create New API Token)
# In Colab, run this cell, and it will prompt you to upload the file.

# Copy the kaggle.json to the correct directory and set permissions
!cp kaggle.json ~/.kaggle/
```

```
!chmod 600 ~/.kaggle/kaggle.json

# Download the dataset in colab
!kaggle datasets download masoudnickparvar/brain-tumor-mri-dataset -p
/content/brain-tumor-mri-dataset --unzip
```

```
Dataset URL: https://www.kaggle.com/datasets/masoudnickparvar/brain-
tumor-mri-dataset
License(s): CC0-1.0
Downloading brain-tumor-mri-dataset.zip to /content/brain-tumor-mri-
dataset
 79% 118M/149M [00:00<00:00, 474MB/s]
100% 149M/149M [00:00<00:00, 528MB/s]
```

```
# Download the dataset locally
!kaggle datasets download masoudnickparvar/brain-tumor-mri-dataset -p
/brain-tumor-mri-dataset --unzip
```

# 2. Importing and Setup of Dependencies

```
# General Imports
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import os
import shutil
import random
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix

# Neural Network imports
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.models import load_model
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Input
from tensorflow.keras.optimizers import Adam

# Image augmentation importrs
from tensorflow.keras.utils import load_img
from tensorflow.keras.preprocessing import image
from tensorflow.keras.layers import RandomRotation
from tensorflow.keras.layers import RandomContrast
from tensorflow.keras.layers import RandomZoom
from tensorflow.keras.layers import RandomFlip
from tensorflow.keras.layers import RandomTranslation
```

```
# Training Model callbacks
from tensorflow.keras.callbacks import ReduceLROnPlateau
from tensorflow.keras.callbacks import ModelCheckpoint

print(f'Tensorflow Version: {tf.__version__}')

SEED = 111

# Data Visualization updates
%config InlineBackend.figure_format = 'retina'
plt.rcParams["figure.figsize"] = (16, 10)
plt.rcParams.update({'font.size': 14})
```

```
Tensorflow Version: 2.18.0
```

```
def get_data_labels(directory, shuffle=True, random_state=0):
    from sklearn.utils import shuffle
    data_path = []
    data_index = []
    label_dict = {label: index for index, label in
enumerate(sorted(os.listdir(directory)))}

    for label, index in label_dict.items():
        label_dir = os.path.join(directory, label)
        for image in os.listdir(label_dir):
            image_path = os.path.join(label_dir, image)
            data_path.append(image_path)
            data_index.append(index)

    if shuffle:
        data_path, data_index = shuffle(data_path, data_index,
random_state=random_state)

    return data_path, data_index

def parse_function(filename, label, image_size, n_channels):
    image_string = tf.io.read_file(filename)
    image = tf.image.decode_jpeg(image_string, n_channels)
    image = tf.image.resize(image, image_size)
    return image, label

def get_dataset(paths, labels, image_size, n_channels=1,
num_classes=4, batch_size=32):
    path_ds = tf.data.Dataset.from_tensor_slices((paths, labels))
    image_label_ds = path_ds.map(lambda path, label:
parse_function(path, label, image_size, n_channels),
                                 num_parallel_calls=tf.data.AUTOTUNE)
    return
image_label_ds.batch(batch_size).prefetch(buffer_size=tf.data.AUTOTUNE
)
```

# 3. Importing Datasets with Validation Split

```
USER_PATH = "/content/brain-tumor-mri-dataset"
# USER_PATH = "brain-tumor-mri-dataset" (LOCAL)
TRAIN_DIR = os.path.join(USER_PATH, 'Training')
TEST_DIR = os.path.join(USER_PATH, 'Testing')
VAL_DIR = os.path.join(USER_PATH, 'Validation')

# Define the percentage of data for the validation set
VALIDATION_SPLIT_PERCENTAGE = 0.03 # At least 3%

# Create Validation directory and its subdirectories if they don't
exist
if not os.path.exists(VAL_DIR):
    os.makedirs(VAL_DIR)

for category in os.listdir(TEST_DIR):
    category_path_testing = os.path.join(TEST_DIR, category)
    category_path_validation = os.path.join(VAL_DIR, category)

    if not os.path.exists(category_path_validation):
        os.makedirs(category_path_validation)

    if os.path.isdir(category_path_testing): # Ensure it's a directory
        images = [img for img in os.listdir(category_path_testing) if
os.path.isfile(os.path.join(category_path_testing, img))]

        # Calculate the number of images for validation
        num_val_images = int(len(images) *
VALIDATION_SPLIT_PERCENTAGE)
        if num_val_images == 0 and len(images) > 0 : # Ensure at least
1 image if possible and 3% is too small
             num_val_images = 1

        # Randomly select images for validation
        val_images_to_move = random.sample(images, num_val_images)

        # Move selected images
        for img_name in val_images_to_move:
            src_path = os.path.join(category_path_testing, img_name)
            dest_path = os.path.join(category_path_validation,
img_name)
            shutil.move(src_path, dest_path)
        print(f"Moved {len(val_images_to_move)} images from
Testing/{category} to Validation/{category}")


# Getting data labels after splitting
train_paths, train_index = get_data_labels(TRAIN_DIR,
random_state=SEED)
test_paths, test_index = get_data_labels(TEST_DIR, random_state=SEED)
```

```python
val_paths, val_index = get_data_labels(VAL_DIR, random_state=SEED)

# Printing training, validation, and testing sample sizes
print('\nTraining')
print(f'Number of Paths: {len(train_paths)}')
print(f'Number of Labels: {len(train_index)}')

print('\nTesting')
print(f'Number of Paths: {len(test_paths)}')
print(f'Number of Labels: {len(test_index)}')

print('\nValidation')
print(f'Number of Paths: {len(val_paths)}')
print(f'Number of Labels: {len(val_index)}')

# Prepare datasets with 4 classes and grayscale
batch_size = 32
image_dim = (168, 168) # height, width
train_ds = get_dataset(train_paths, train_index, image_dim,
n_channels=1, num_classes=4, batch_size=batch_size)
test_ds = get_dataset(test_paths, test_index, image_dim, n_channels=1,
num_classes=4, batch_size=batch_size)
val_ds = get_dataset(val_paths, val_index, image_dim, n_channels=1,
num_classes=4, batch_size=batch_size)
# Output to show datasets
print(f"\nTraining dataset: {train_ds}")
print(f"\nTesting dataset: {test_ds}")
print(f"\nValidation dataset: {val_ds}")

# Class mappings - ensure these match the folder names alphabetically
after get_data_labels sorts them
# The label_dict in get_data_labels will be {'glioma':0,
'meningioma':1, 'notumor':2, 'pituitary':3}
# if your folders are named exactly like that.
class_mappings = {label: index for index, label in
enumerate(sorted(os.listdir(TRAIN_DIR)))}
inv_class_mappings = {v: k for k, v in class_mappings.items()}
class_names = list(class_mappings.keys()) # Will be ['glioma',
'meningioma', 'notumor', 'pituitary'] if sorted

print(f"\nClass Mappings used by get_data_labels: {class_mappings}")
print(f"Class Names for plotting (derived from mappings):
{class_names}")
```

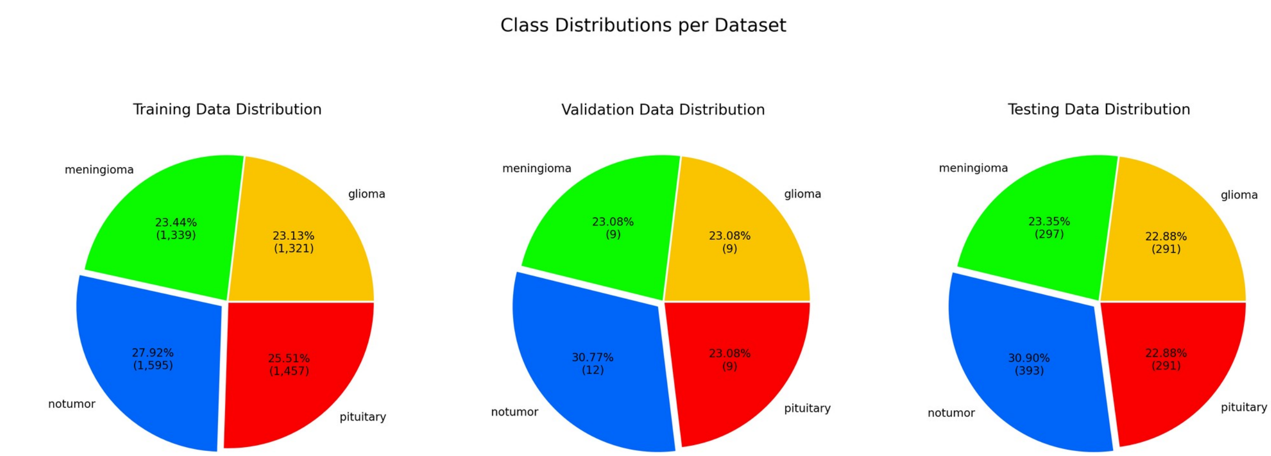
```
Moved 9 images from Testing/pituitary to Validation/pituitary
Moved 12 images from Testing/notumor to Validation/notumor
Moved 9 images from Testing/glioma to Validation/glioma
Moved 9 images from Testing/meningioma to Validation/meningioma

Training
```

```
Number of Paths: 5712
Number of Labels: 5712

Testing
Number of Paths: 1272
Number of Labels: 1272

Validation
Number of Paths: 39
Number of Labels: 39

Training dataset: <_PrefetchDataset
element_spec=(TensorSpec(shape=(None, 168, 168, 1), dtype=tf.float32,
name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>

Testing dataset: <_PrefetchDataset
element_spec=(TensorSpec(shape=(None, 168, 168, 1), dtype=tf.float32,
name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>

Validation dataset: <_PrefetchDataset
element_spec=(TensorSpec(shape=(None, 168, 168, 1), dtype=tf.float32,
name=None), TensorSpec(shape=(None,), dtype=tf.int32, name=None))>

Class Mappings used by get_data_labels: {'glioma': 0, 'meningioma': 1,
'notumor': 2, 'pituitary': 3}
Class Names for plotting (derived from mappings): ['glioma',
'meningioma', 'notumor', 'pituitary']
```

# 4. Data Visualization

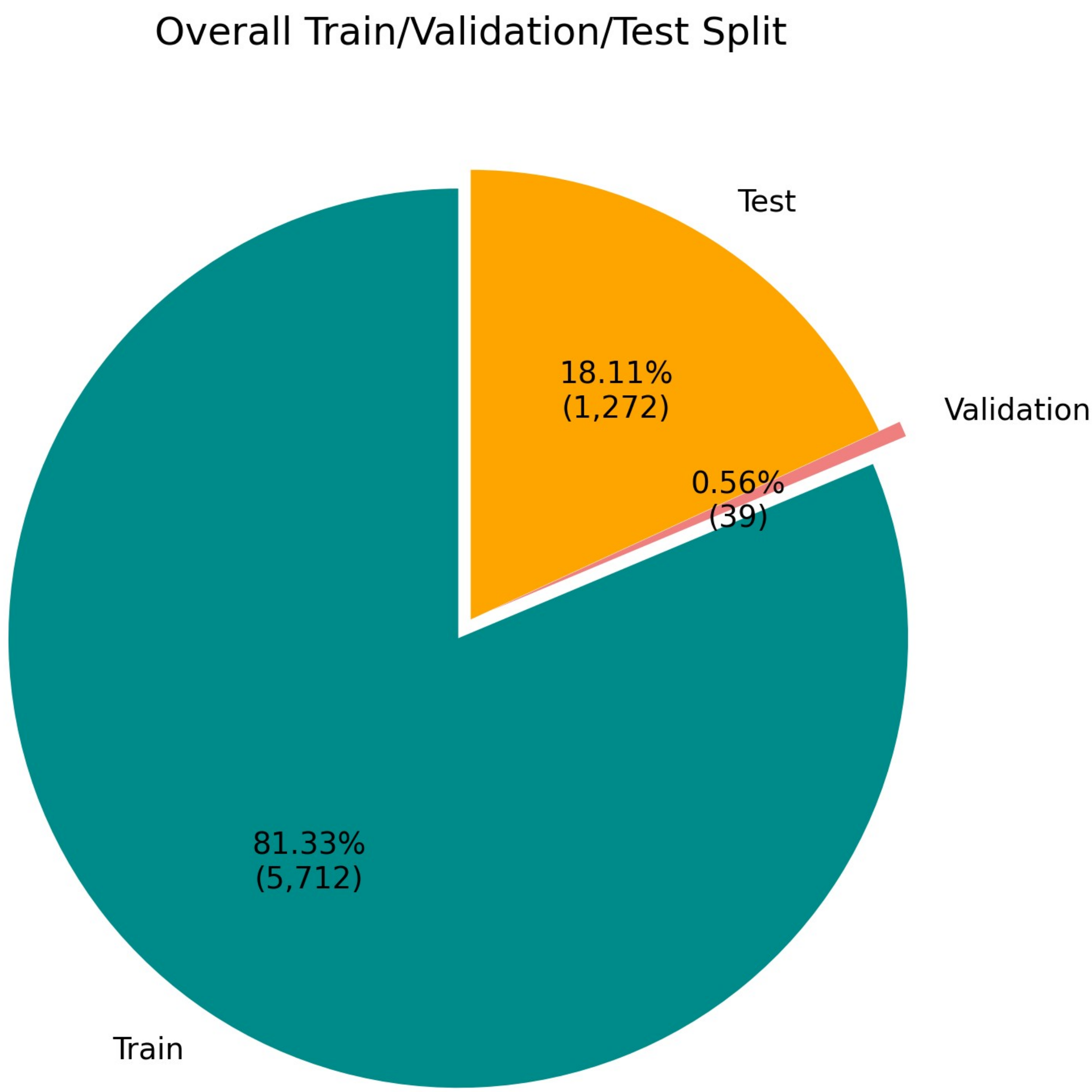
```
# Figure 1: Class Distributions (Training, Validation, Testing)
fig1, ax1 = plt.subplots(nrows=1, ncols=3, figsize=(24, 8))
plt.subplots_adjust(wspace=0.2)

train_class_counts = [len([x for x in train_index if x ==
class_mappings[name]]) for name in class_names]
ax1[0].set_title('Training Data Distribution', fontsize=16)
ax1[0].pie(
    train_class_counts,
    labels=class_names,
    colors=['#FAC500','#0BFA00', '#0066FA','#FA0000'],
    autopct=lambda p: '{:.2f}%\n({:,.0f})'.format(p, p *
sum(train_class_counts) / 100),
    explode=(0.01, 0.01, 0.05, 0.01),
    textprops={'fontsize': 12}
)

val_class_counts = [len([x for x in val_index if x ==
class_mappings[name]]) for name in class_names]
ax1[1].set_title('Validation Data Distribution', fontsize=16)
```

```
ax1[1].pie(
    val_class_counts,
    labels=class_names,
    colors=['#FAC500','#0BFA00', '#0066FA','#FA0000'],
    autopct=lambda p: '{:.2f}%\n({:,.0f})'.format(p, p *
sum(val_class_counts) / 100),
    explode=(0.01, 0.01, 0.05, 0.01),
    textprops={'fontsize': 12}
)

test_class_counts = [len([x for x in test_index if x ==
class_mappings[name]]) for name in class_names]
ax1[2].set_title('Testing Data Distribution', fontsize=16)
ax1[2].pie(
    test_class_counts,
    labels=class_names,
    colors=['#FAC500', '#0BFA00', '#0066FA', '#FA0000'],
    autopct=lambda p: '{:.2f}%\n({:,.0f})'.format(p, p *
sum(test_class_counts) / 100),
    explode=(0.01, 0.01, 0.05, 0.01),
    textprops={'fontsize': 12}
)

fig1.suptitle('Class Distributions per Dataset', fontsize=20, y=1.03)
plt.show()
```



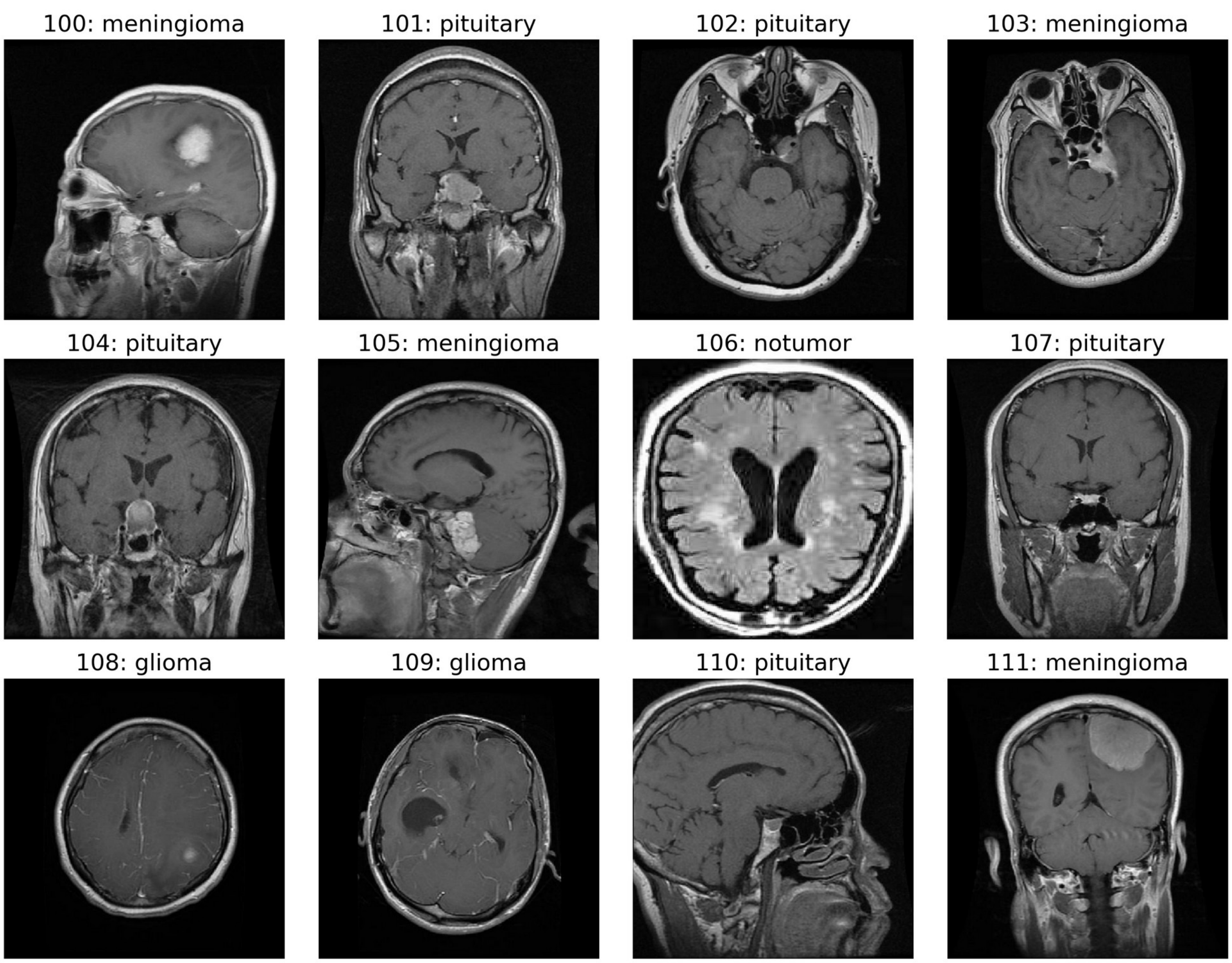

```
# Figure 2: Train/Validation/Test Split
fig2, ax2 = plt.subplots(figsize=(10, 8))

split_counts = [len(train_index), len(val_index), len(test_index)]
split_labels = ['Train', 'Validation', 'Test']
split_colors = ['darkcyan', 'lightcoral', 'orange']
split_explode = (0.05, 0.05, 0)
```

```
ax2.set_title('Overall Train/Validation/Test Split', fontsize=18)
ax2.pie(
    split_counts,
    labels=split_labels,
    colors=split_colors,
    autopct=lambda p: '{:.2f}%\n({:,.0f})'.format(p, p *
sum(split_counts) / 100),
    explode=split_explode,
    startangle=90,
    textprops={'fontsize': 14}
)
fig2.tight_layout()
plt.show()
```




```
# Function to display a list of images based on the given index
def show_images(paths, label_paths, class_mappings,
index_list=range(10), im_size=250, figsize=(12, 8)):

    num_images = len(index_list)
    num_rows = (num_images + 3) // 4
    index_to_class = {v: k for k, v in class_mappings.items()}
    _, ax = plt.subplots(nrows=num_rows, ncols=4, figsize=figsize)
    ax = ax.flatten()

    for i, index in enumerate(index_list):
        if i >= num_images:
            break
```

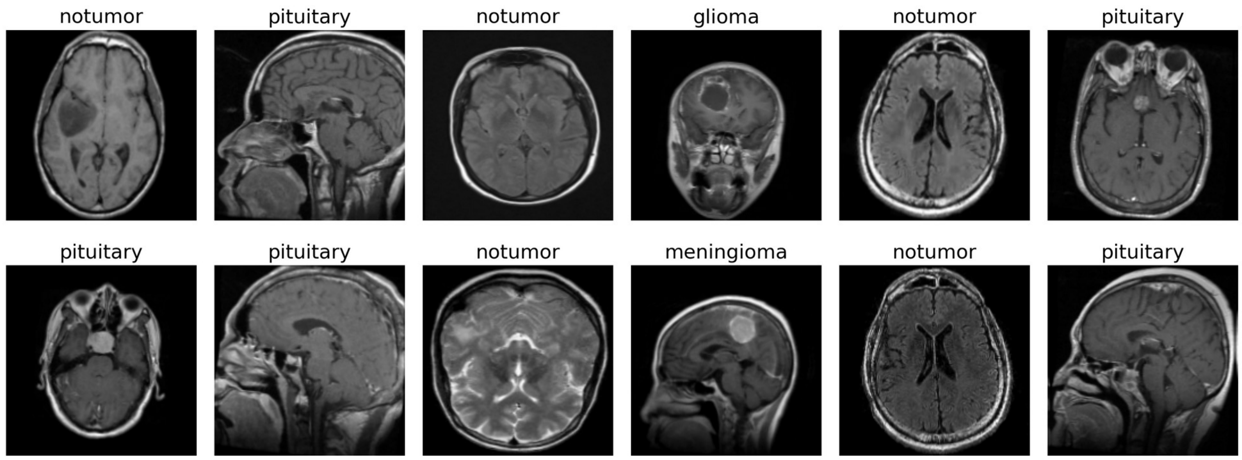
```
        image = load_img(paths[index], target_size=(im_size, im_size),
color_mode='grayscale')
        ax[i].imshow(image, cmap='Greys_r')
        class_name = index_to_class[label_paths[index]]
        ax[i].set_title(f'{index}: {class_name}')
        ax[i].axis('off')

    plt.tight_layout()
    plt.show()

# Four images from different angles
show_images(train_paths, train_index, class_mappings, im_size=350,
figsize=(13,10),
            index_list=range(100, 112))
```




# 5. Data Preprocessing & Training Setup Values

```
# Data augmentation sequential model
data_augmentation = Sequential([
    # RandomFlip("horizontal_and_vertical"),
```

```
    RandomFlip("horizontal"),
    RandomRotation(0.02, fill_mode='constant'),
    RandomContrast(0.1),
    RandomZoom(height_factor=0.01, width_factor=0.05),
    RandomTranslation(height_factor=0.0015, width_factor=0.0015,
fill_mode='constant'),
])

# Training augmentation and nornalization
def preprocess_train(image, label):
    # Apply data augmentation and Normalize
    image = data_augmentation(image) / 255.0
    return image, label

# For test dataset only appying normalization
def preprocess_test(image, label):
    return image / 255.0, label

# Apply transformation to training and testing datasets
train_ds_preprocessed = train_ds.map(preprocess_train,
num_parallel_calls=tf.data.AUTOTUNE)
test_ds_preprocessed = test_ds.map(preprocess_test,
num_parallel_calls=tf.data.AUTOTUNE)

# Function to display augmented images
def plot_augmented_images(dataset, shape, class_mappings, figsize=(15,
6)):
    plt.figure(figsize=figsize)
    index_to_class = {v: k for k, v in class_mappings.items()}
    for images, label in dataset.take(1):
        i = 0
        for i in range(shape[0]*shape[1]):
            ax = plt.subplot(shape[0], shape[1], i + 1)
            plt.imshow(images[i].numpy().squeeze(), cmap='gray')
            plt.title(index_to_class[label.numpy()[i]])
            plt.axis("off")
            i += 1

    plt.tight_layout()
    plt.show()

# Displaying augmented images
plot_augmented_images(train_ds_preprocessed, shape=(2, 6),
class_mappings=class_mappings)
```




```
# Classes and Image shape: height, width, grayscale
num_classes = len(class_mappings.keys())
image_shape = (image_dim[0], image_dim[1], 1)

# Training epochs and batch size
epochs = 50
print(f'Number of Classes: {num_classes}')
print(f'Image shape: {image_shape}')
print(f'Epochs: {epochs}')
print(f'Batch size: {batch_size}')

def encode_labels(image, label):
    return image, tf.one_hot(label, depth=num_classes)

train_ds_preprocessed = train_ds_preprocessed.map(encode_labels,
num_parallel_calls=tf.data.AUTOTUNE)
test_ds_preprocessed = test_ds_preprocessed.map(encode_labels,
num_parallel_calls=tf.data.AUTOTUNE)

Number of Classes: 4
Image shape: (168, 168, 1)
Epochs: 50
Batch size: 32
```

# 6. Model Training and Analysis

```
# Building model
model = Sequential([
    # Input tensor shape
    Input(shape=image_shape),

    # Convolutional layer 1
    Conv2D(64, (5, 5), activation="relu"),
    MaxPooling2D(pool_size=(3, 3)),
```

```
    # Convolutional layer 2
    Conv2D(64, (5, 5), activation="relu"),
    MaxPooling2D(pool_size=(3, 3)),

    # Convolutional layer 3
    Conv2D(128, (4, 4), activation="relu"),
    MaxPooling2D(pool_size=(2, 2)),

    # Convolutional layer 4
    Conv2D(128, (4, 4), activation="relu"),
    MaxPooling2D(pool_size=(2, 2)),
    Flatten(),

    # Dense layers
    Dense(512, activation="relu"),
    Dense(num_classes, activation="softmax")
])

# Model summary
model.summary()

# COompilng model with Adam optimizer
optimizer = Adam(learning_rate=0.001, beta_1=0.85, beta_2=0.9925)
model.compile(optimizer=optimizer, loss='categorical_crossentropy',
metrics= ['accuracy'])

Model: "sequential_1"

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━━━━━┓
┃ Layer (type)                     ┃ Output Shape           ┃
Param # ┃
┡━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━━━━━━━━━━━━━━━━━╇━━━━━━━━
━━━━━┩
│ conv2d (Conv2D)                  │ (None, 164, 164, 64)   │
1,664 │
├──────────────────────────────────┼────────────────────────┼────────
─────┤
│ max_pooling2d (MaxPooling2D)     │ (None, 54, 54, 64)     │
0 │
├──────────────────────────────────┼────────────────────────┼────────
─────┤
│ conv2d_1 (Conv2D)                │ (None, 50, 50, 64)     │
102,464 │
├──────────────────────────────────┼────────────────────────┼────────
─────┤
│ max_pooling2d_1 (MaxPooling2D)   │ (None, 16, 16, 64)     │
0 │
├──────────────────────────────────┼────────────────────────┼────────
─────┤
```

```
│ conv2d_2 (Conv2D)                  │ (None, 13, 13, 128)      │
131,200 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_2 (MaxPooling2D)     │ (None, 6, 6, 128)        │
0 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ conv2d_3 (Conv2D)                  │ (None, 3, 3, 128)        │
262,272 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ max_pooling2d_3 (MaxPooling2D)     │ (None, 1, 1, 128)        │
0 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ flatten (Flatten)                  │ (None, 128)              │
0 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dense (Dense)                      │ (None, 512)              │
66,048 │
├────────────────────────────────────┼──────────────────────────┼──────────
───────┤
│ dense_1 (Dense)                    │ (None, 4)                │
2,052 │
└────────────────────────────────────┴──────────────────────────┴──────────
───────┘

 Total params: 565,700 (2.16 MB)

 Trainable params: 565,700 (2.16 MB)

 Non-trainable params: 0 (0.00 B)

# Custom callback for reducing learning rate at accuracy values
class ReduceLROnMultipleAccuracies(tf.keras.callbacks.Callback):
    def __init__(self, thresholds, factor, monitor='val_accuracy',
verbose=1):
        super(ReduceLROnMultipleAccuracies, self).__init__()
        self.thresholds = thresholds  # List of accuracy thresholds
        self.factor = factor  # Factor to reduce the learning rate
        self.monitor = monitor
        self.verbose = verbose
        self.thresholds_reached = [False] * len(thresholds)  # Track
each threshold

    def on_epoch_end(self, epoch, logs=None):
        current_accuracy = logs.get(self.monitor)
        for i, threshold in enumerate(self.thresholds):
```

```
            if current_accuracy >= threshold and not
self.thresholds_reached[i]:
                optimizer = self.model.optimizer
                old_lr = optimizer.learning_rate.numpy()
                new_lr = old_lr * self.factor
                optimizer.learning_rate.assign(new_lr)
                self.thresholds_reached[i] = True  # Mark this
threshold as reached
                if self.verbose > 0:
                    print(f"\nEpoch {epoch+1}: {self.monitor} reached
{threshold}. Reducing learning rate from {old_lr} to {new_lr}.")

# Try a custom callback
thresholds = [0.96, 0.99, 0.9935]
lr_callback = ReduceLROnMultipleAccuracies(thresholds=thresholds,
factor=0.75, monitor='val_accuracy', verbose=False)

# Callbacks for improved covergence of gradient and best test accuracy
model_rlr = ReduceLROnPlateau(monitor='val_loss', factor=0.8,
min_lr=1e-4, patience=4, verbose=False)
model_mc = ModelCheckpoint('model.keras', monitor='val_accuracy',
mode='max', save_best_only=True, verbose=False)

# Training the model
history = model.fit(
    train_ds_preprocessed,
    epochs=epochs,
    validation_data=test_ds_preprocessed,
    callbacks=[model_rlr, model_mc],
    verbose=True
)
```

```
Epoch 1/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 31s 136ms/step - accuracy: 0.5143 - loss:
1.0642 - val_accuracy: 0.7170 - val_loss: 0.6974 - learning_rate:
0.0010
Epoch 2/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 22s 124ms/step - accuracy: 0.8123 - loss:
0.4898 - val_accuracy: 0.8514 - val_loss: 0.4033 - learning_rate:
0.0010
Epoch 3/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 111ms/step - accuracy: 0.8711 - loss:
0.3362 - val_accuracy: 0.8813 - val_loss: 0.3055 - learning_rate:
0.0010
Epoch 4/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 101ms/step - accuracy: 0.9027 - loss:
0.2625 - val_accuracy: 0.8978 - val_loss: 0.2459 - learning_rate:
0.0010
Epoch 5/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 22s 109ms/step - accuracy: 0.9354 - loss:
```

```
0.1779 - val_accuracy: 0.9167 - val_loss: 0.2435 - learning_rate:
0.0010
Epoch 6/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 99ms/step - accuracy: 0.9511 - loss:
0.1393 - val_accuracy: 0.9159 - val_loss: 0.2148 - learning_rate:
0.0010
Epoch 7/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 107ms/step - accuracy: 0.9526 - loss:
0.1295 - val_accuracy: 0.8860 - val_loss: 0.3381 - learning_rate:
0.0010
Epoch 8/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9583 - loss:
0.1162 - val_accuracy: 0.8805 - val_loss: 0.3446 - learning_rate:
0.0010
Epoch 9/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 104ms/step - accuracy: 0.9610 - loss:
0.1012 - val_accuracy: 0.9347 - val_loss: 0.1899 - learning_rate:
0.0010
Epoch 10/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 101ms/step - accuracy: 0.9692 - loss:
0.0871 - val_accuracy: 0.9222 - val_loss: 0.2600 - learning_rate:
0.0010
Epoch 11/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 106ms/step - accuracy: 0.9760 - loss:
0.0724 - val_accuracy: 0.9230 - val_loss: 0.2419 - learning_rate:
0.0010
Epoch 12/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 102ms/step - accuracy: 0.9757 - loss:
0.0694 - val_accuracy: 0.9395 - val_loss: 0.1648 - learning_rate:
0.0010
Epoch 13/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 103ms/step - accuracy: 0.9777 - loss:
0.0648 - val_accuracy: 0.9379 - val_loss: 0.2082 - learning_rate:
0.0010
Epoch 14/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 100ms/step - accuracy: 0.9841 - loss:
0.0484 - val_accuracy: 0.9458 - val_loss: 0.1467 - learning_rate:
0.0010
Epoch 15/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 101ms/step - accuracy: 0.9838 - loss:
0.0539 - val_accuracy: 0.9426 - val_loss: 0.2026 - learning_rate:
0.0010
Epoch 16/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 102ms/step - accuracy: 0.9824 - loss:
0.0616 - val_accuracy: 0.9591 - val_loss: 0.1142 - learning_rate:
0.0010
Epoch 17/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 21s 108ms/step - accuracy: 0.9826 - loss:
0.0481 - val_accuracy: 0.9536 - val_loss: 0.1404 - learning_rate:
```

```
0.0010
Epoch 18/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 99ms/step - accuracy: 0.9891 - loss:
0.0289 - val_accuracy: 0.9489 - val_loss: 0.1490 - learning_rate:
0.0010
Epoch 19/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 105ms/step - accuracy: 0.9841 - loss:
0.0494 - val_accuracy: 0.9662 - val_loss: 0.1043 - learning_rate:
0.0010
Epoch 20/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 104ms/step - accuracy: 0.9767 - loss:
0.0612 - val_accuracy: 0.9638 - val_loss: 0.1533 - learning_rate:
0.0010
Epoch 21/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 104ms/step - accuracy: 0.9872 - loss:
0.0364 - val_accuracy: 0.9662 - val_loss: 0.0981 - learning_rate:
0.0010
Epoch 22/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 102ms/step - accuracy: 0.9905 - loss:
0.0256 - val_accuracy: 0.9709 - val_loss: 0.0821 - learning_rate:
0.0010
Epoch 23/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 21s 104ms/step - accuracy: 0.9866 - loss:
0.0358 - val_accuracy: 0.9654 - val_loss: 0.1204 - learning_rate:
0.0010
Epoch 24/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 98ms/step - accuracy: 0.9877 - loss:
0.0398 - val_accuracy: 0.9717 - val_loss: 0.0937 - learning_rate:
0.0010
Epoch 25/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 105ms/step - accuracy: 0.9888 - loss:
0.0406 - val_accuracy: 0.9709 - val_loss: 0.0930 - learning_rate:
0.0010
Epoch 26/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9919 - loss:
0.0252 - val_accuracy: 0.9717 - val_loss: 0.1024 - learning_rate:
0.0010
Epoch 27/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 22s 108ms/step - accuracy: 0.9936 - loss:
0.0197 - val_accuracy: 0.9803 - val_loss: 0.0647 - learning_rate:
8.0000e-04
Epoch 28/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9951 - loss:
0.0127 - val_accuracy: 0.9725 - val_loss: 0.0944 - learning_rate:
8.0000e-04
Epoch 29/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 105ms/step - accuracy: 0.9929 - loss:
0.0226 - val_accuracy: 0.9835 - val_loss: 0.0604 - learning_rate:
8.0000e-04
```

```
Epoch 30/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 99ms/step - accuracy: 0.9913 - loss:
0.0251 - val_accuracy: 0.9858 - val_loss: 0.0729 - learning_rate:
8.0000e-04
Epoch 31/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 22s 107ms/step - accuracy: 0.9950 - loss:
0.0108 - val_accuracy: 0.9843 - val_loss: 0.0586 - learning_rate:
8.0000e-04
Epoch 32/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 102ms/step - accuracy: 0.9978 - loss:
0.0078 - val_accuracy: 0.9434 - val_loss: 0.3073 - learning_rate:
8.0000e-04
Epoch 33/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 101ms/step - accuracy: 0.9945 - loss:
0.0224 - val_accuracy: 0.9843 - val_loss: 0.0649 - learning_rate:
8.0000e-04
Epoch 34/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 21s 106ms/step - accuracy: 0.9961 - loss:
0.0090 - val_accuracy: 0.9929 - val_loss: 0.0389 - learning_rate:
8.0000e-04
Epoch 35/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 100ms/step - accuracy: 0.9924 - loss:
0.0249 - val_accuracy: 0.9953 - val_loss: 0.0453 - learning_rate:
8.0000e-04
Epoch 36/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 106ms/step - accuracy: 0.9953 - loss:
0.0195 - val_accuracy: 0.9898 - val_loss: 0.0425 - learning_rate:
8.0000e-04
Epoch 37/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9964 - loss:
0.0098 - val_accuracy: 0.9772 - val_loss: 0.0806 - learning_rate:
8.0000e-04
Epoch 38/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 102ms/step - accuracy: 0.9932 - loss:
0.0178 - val_accuracy: 0.9803 - val_loss: 0.0820 - learning_rate:
8.0000e-04
Epoch 39/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 101ms/step - accuracy: 0.9971 - loss:
0.0061 - val_accuracy: 0.9874 - val_loss: 0.0588 - learning_rate:
6.4000e-04
Epoch 40/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9931 - loss:
0.0218 - val_accuracy: 0.9929 - val_loss: 0.0470 - learning_rate:
6.4000e-04
Epoch 41/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 104ms/step - accuracy: 0.9992 - loss:
0.0023 - val_accuracy: 0.9819 - val_loss: 0.0743 - learning_rate:
6.4000e-04
Epoch 42/50
```

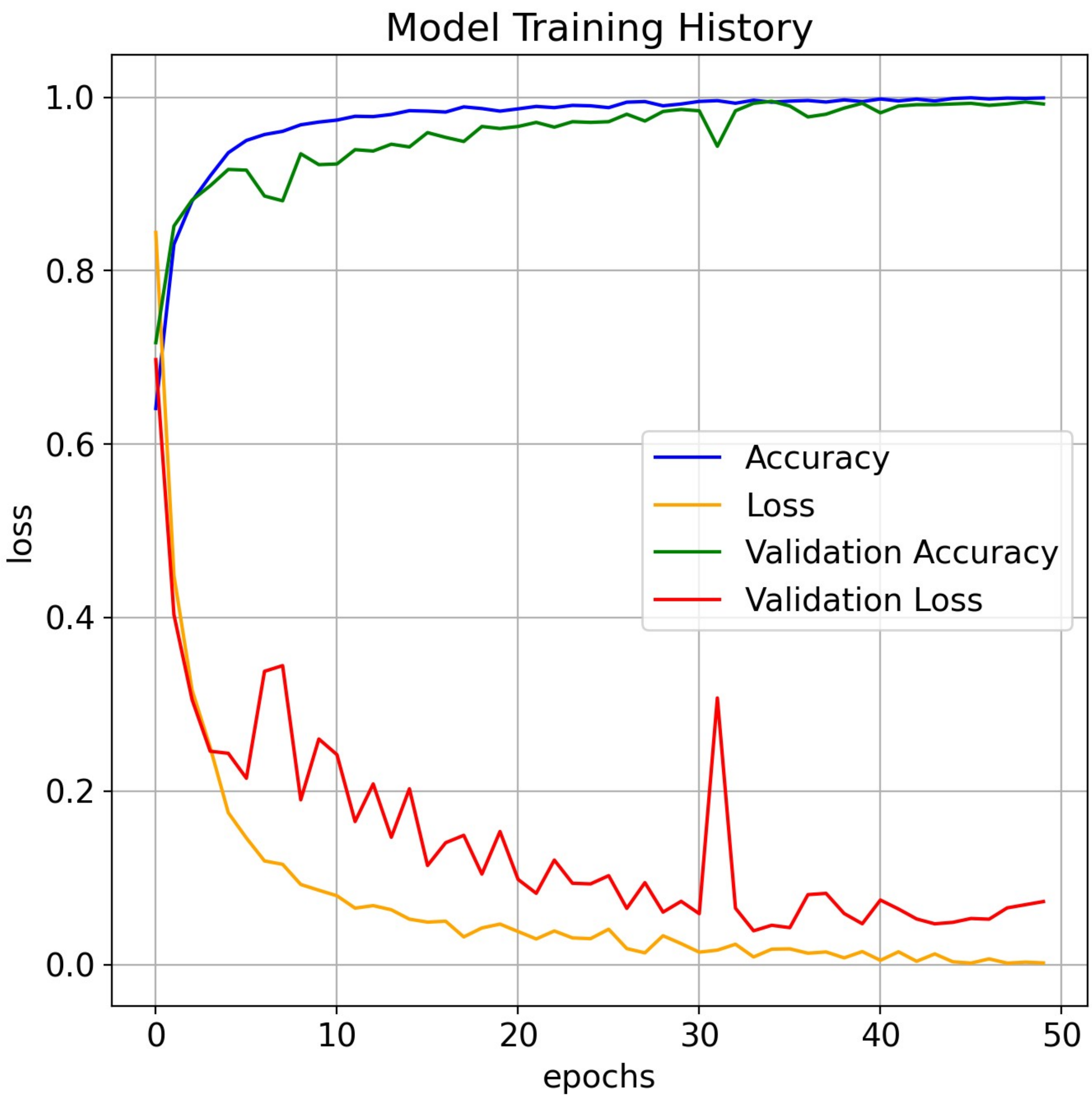
```
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 98ms/step - accuracy: 0.9927 - loss: 
0.0207 - val_accuracy: 0.9898 - val_loss: 0.0640 - learning_rate: 
6.4000e-04
Epoch 43/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 21s 102ms/step - accuracy: 0.9971 - loss: 
0.0043 - val_accuracy: 0.9914 - val_loss: 0.0525 - learning_rate: 
5.1200e-04
Epoch 44/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 101ms/step - accuracy: 0.9964 - loss: 
0.0091 - val_accuracy: 0.9914 - val_loss: 0.0469 - learning_rate: 
5.1200e-04
Epoch 45/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 108ms/step - accuracy: 0.9985 - loss: 
0.0031 - val_accuracy: 0.9921 - val_loss: 0.0486 - learning_rate: 
5.1200e-04
Epoch 46/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 19s 102ms/step - accuracy: 0.9994 - loss: 
0.0013 - val_accuracy: 0.9929 - val_loss: 0.0531 - learning_rate: 
5.1200e-04
Epoch 47/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 99ms/step - accuracy: 0.9984 - loss: 
0.0055 - val_accuracy: 0.9906 - val_loss: 0.0523 - learning_rate: 
4.0960e-04
Epoch 48/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 18s 99ms/step - accuracy: 0.9991 - loss: 
0.0014 - val_accuracy: 0.9921 - val_loss: 0.0653 - learning_rate: 
4.0960e-04
Epoch 49/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 99ms/step - accuracy: 0.9988 - loss: 
0.0029 - val_accuracy: 0.9945 - val_loss: 0.0690 - learning_rate: 
4.0960e-04
Epoch 50/50
179/179 ━━━━━━━━━━━━━━━━━━━━ 20s 109ms/step - accuracy: 0.9994 - loss: 
0.0012 - val_accuracy: 0.9921 - val_loss: 0.0726 - learning_rate: 
4.0960e-04
```

```python
# Loading saved model
model = load_model('model.keras')

# Evaluate model and test data accuracy
test_loss, test_acc = model.evaluate(test_ds_preprocessed)
print(f"Test accuracy: {test_acc*100:0.4f}%")
```

```
40/40 ━━━━━━━━━━━━━━━━━━━━ 2s 25ms/step - accuracy: 0.9937 - loss: 
0.0521
Test accuracy: 99.5283%
```

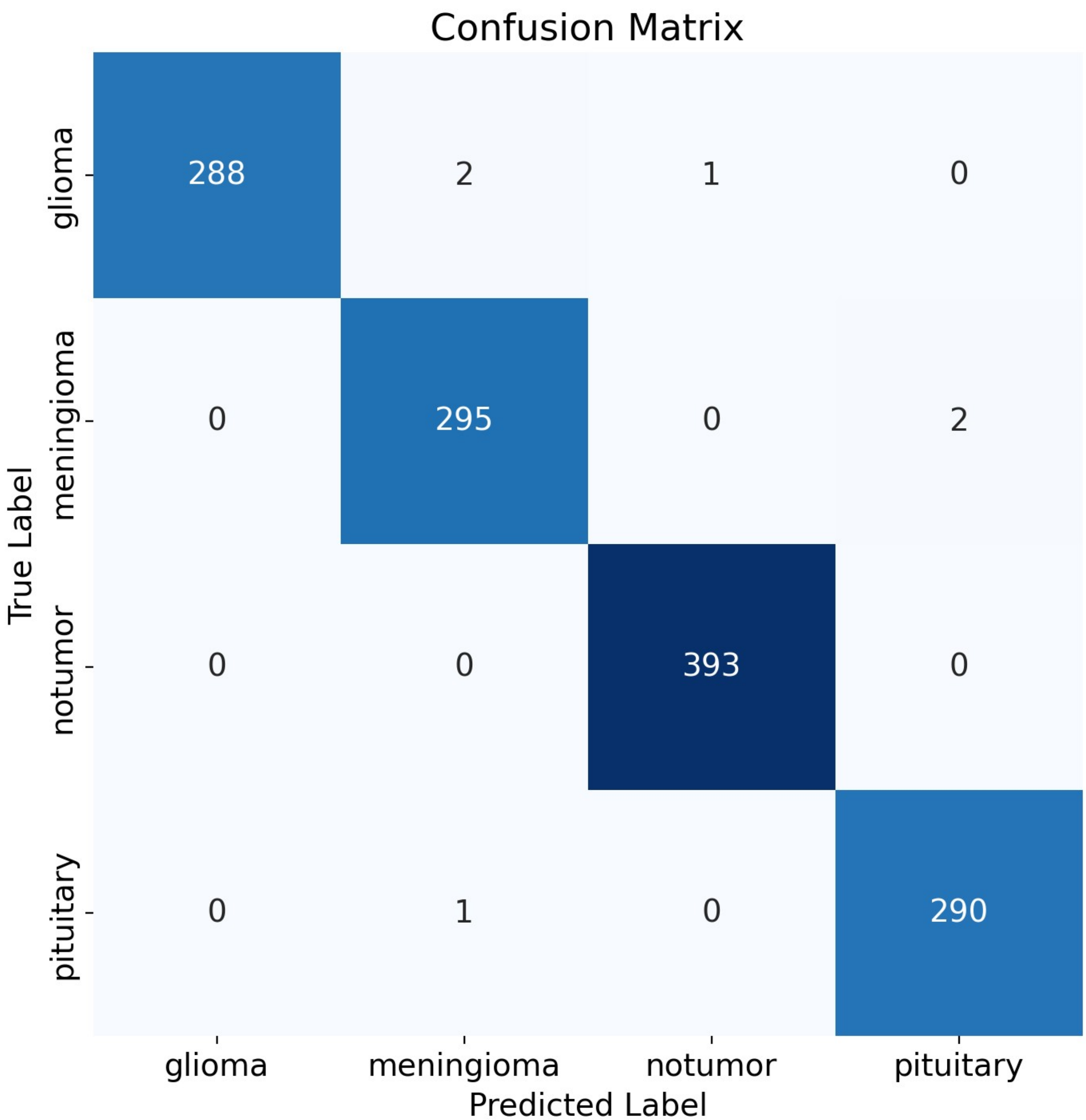
```python
plt.figure(figsize=(7, 7))

# Plotting training and validation metrics
```

```
plt.plot(history.history['accuracy'], color='blue', linestyle='-',
label='Accuracy')
plt.plot(history.history['loss'], color='orange', linestyle='-',
label='Loss')
plt.plot(history.history['val_accuracy'], color='green',
linestyle='-', label='Validation Accuracy')
plt.plot(history.history['val_loss'], color='red', linestyle='-',
label='Validation Loss')

plt.title('Model Training History')
plt.xlabel('epochs')
plt.ylabel('loss')

plt.legend(loc='best')
plt.grid(True)

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




```python
# Using test data for true and preductions
true_labels = []
predicted_labels = []

# Iterate over dataset to collect predictions and true labels
# Unbatch to get sample-wise prediction
for images, labels in test_ds_preprocessed.unbatch():
    # Store true labels (Convert one-hot to index)
    true_label = np.argmax(labels.numpy())
    true_labels.append(true_label)

    # Get model prediction (Predict expects batch dimension)
```

```
    pred = model.predict(tf.expand_dims(images, 0), verbose=False)
    predicted_label = np.argmax(pred)
    predicted_labels.append(predicted_label)

def plot_confusion_matrix(true_labels, predicted_labels,
class_mappings, metrics=False, cmap='Blues'):
    # Compute  confusion matrix
    cm = confusion_matrix(true_labels, predicted_labels)
    plt.figure(figsize=(8, 8))
    sns.heatmap(cm, annot=True, fmt="d", cmap=cmap, cbar=False)
    plt.title("Confusion Matrix")
    plt.xlabel("Predicted Label")
    plt.ylabel("True Label")

    # Mapping of indices to class names in class_mappings
    plt.xticks(ticks=np.arange(num_classes) + 0.5,
labels=class_mappings.keys(), ha='center')
    plt.yticks(ticks=np.arange(num_classes) + 0.5,
labels=class_mappings.keys(), va='center')
    plt.show()

    if metrics:
        # Precision, Recall, and F1-Score for each class & Overall
accuracy
        precision = np.diag(cm) / np.sum(cm, axis=0)
        recall = np.diag(cm) / np.sum(cm, axis=1)
        f1_scores = 2 * precision * recall / (precision + recall)
        accuracy = np.sum(np.diag(cm)) / np.sum(cm)

        print("Class-wise metrics:")
        for i in range(len(class_mappings)):
            class_name = list(class_mappings.keys())[i]
            print(f"\033[94mClass: {class_name}\033[0m")
            print(f"Precision: {precision[i]:.4f}")
            print(f"Recall: {recall[i]:.4f}")
            print(f"F1-Score: {f1_scores[i]:.4f}\n")

        print(f"\033[92mOverall Accuracy: {accuracy:.4f}\033[0m")

# Confusion matrix and netrics from predictions
plot_confusion_matrix(true_labels,
                      predicted_labels,
                      class_mappings,
                      metrics=True)
```

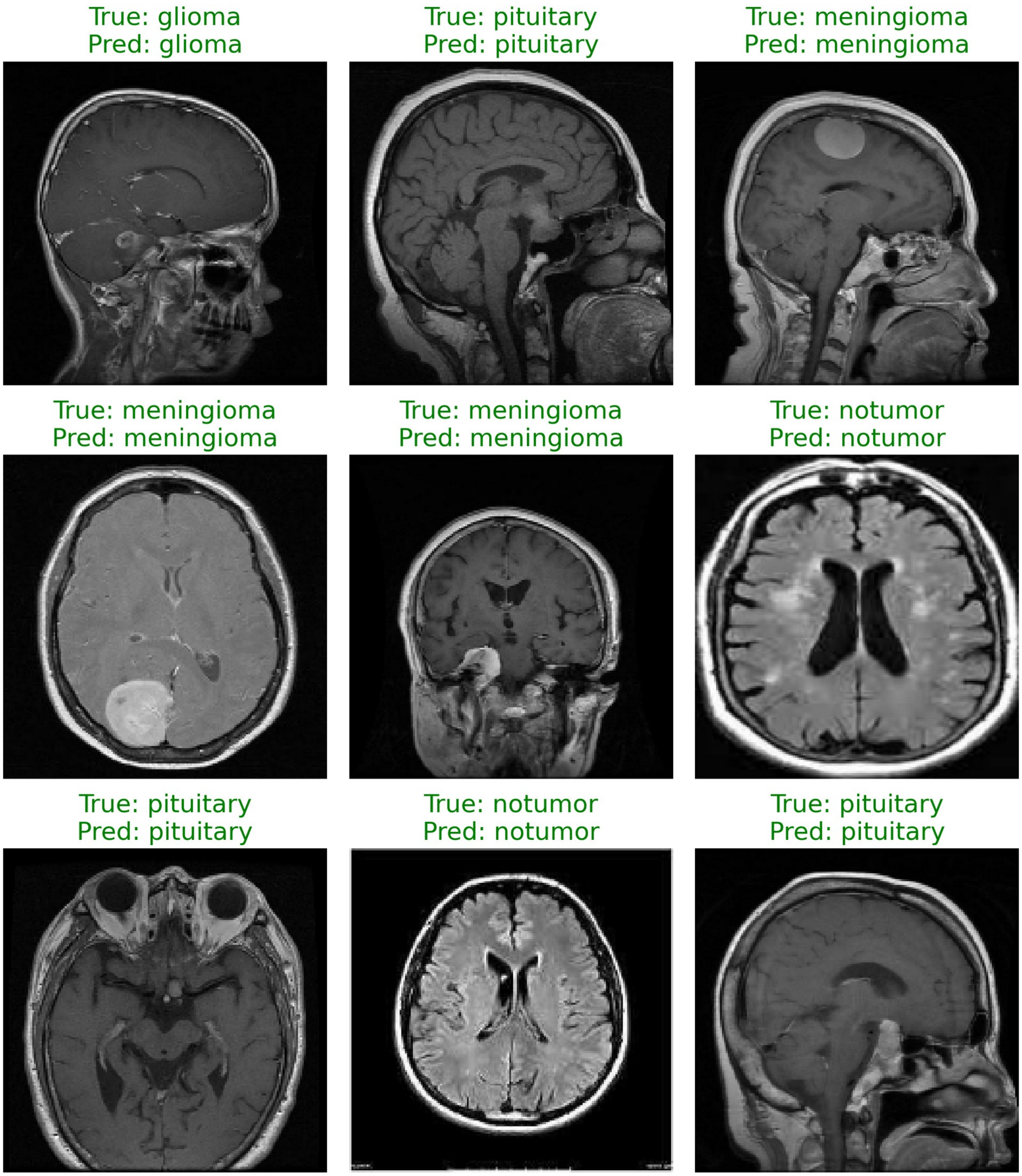



```
Class-wise metrics:
Class: glioma
Precision: 1.0000
Recall: 0.9897
F1-Score: 0.9948

Class: meningioma
Precision: 0.9899
Recall: 0.9933
F1-Score: 0.9916
```

```
Class: notumor
Precision: 0.9975
Recall: 1.0000
F1-Score: 0.9987

Class: pituitary
Precision: 0.9932
Recall: 0.9966
F1-Score: 0.9949

Overall Accuracy: 0.9953
```

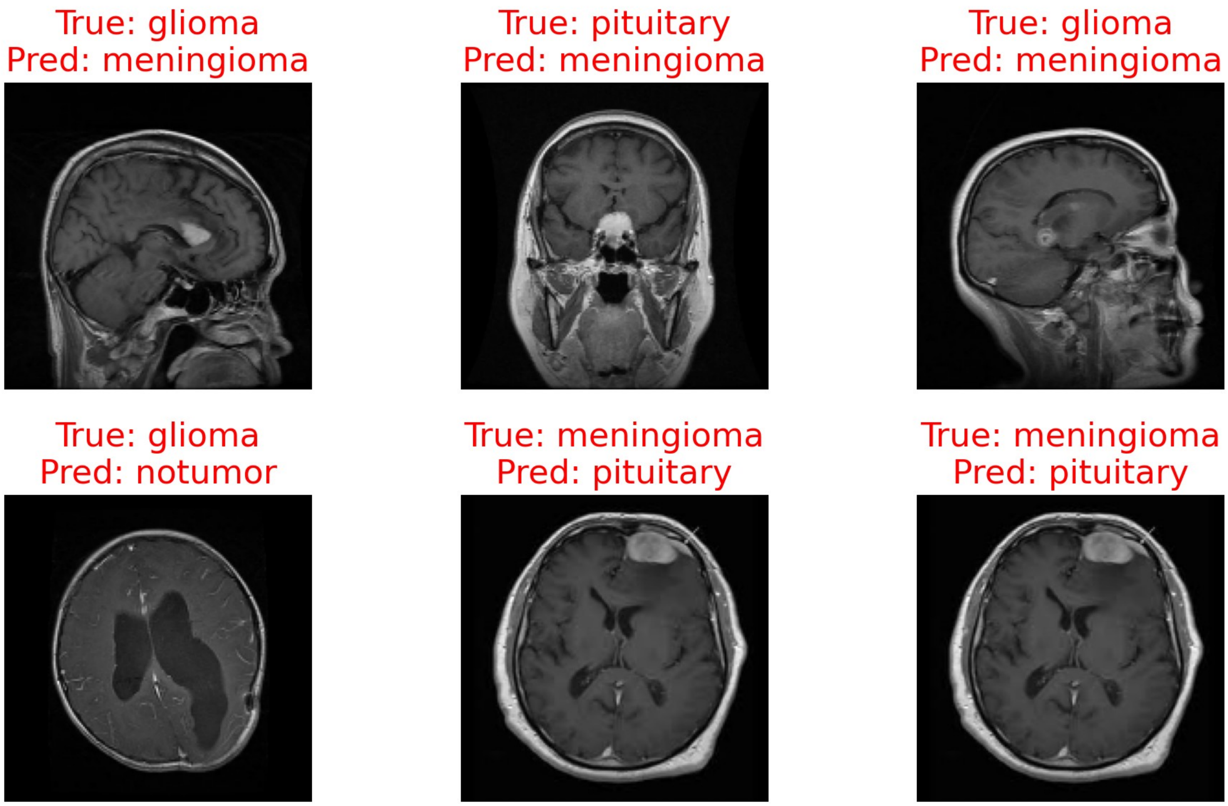
# 7. Model Testing and Deployment

```
def plot_sample_predictions(model, dataset, index_to_class,
num_samples=9, figsize=(13, 12)):
    plt.figure(figsize=figsize)
    num_rows = num_cols = int(np.sqrt(num_samples))

    iterator = iter(dataset.unbatch())

    for i in range(1, num_samples + 1):
        image, true_label = next(iterator)
        image_batch = tf.expand_dims(image, 0)
        predictions = model.predict(image_batch, verbose=False)
        predicted_label = np.argmax(predictions, axis=1)[0]

        true_class_index = np.argmax(true_label.numpy())
        true_class = index_to_class[true_class_index]
        predicted_class = index_to_class[predicted_label]

        # Determine title color based on prediction accuracy
        title_color = 'green' if true_class_index == predicted_label
else 'red'

        plt.subplot(num_rows, num_cols, i)
        plt.imshow(image.numpy().squeeze(), cmap='gray')
        plt.title(f"True: {true_class}\nPred: {predicted_class}",
color=title_color)
        plt.axis('off')

    plt.tight_layout()
    plt.show()

# Plottinng samples with predictions
plot_sample_predictions(model=model,
                        dataset=test_ds_preprocessed,
                        index_to_class=inv_class_mappings,
                        num_samples=9,
                        figsize=(10, 11.5))
```




```
def plot_misclassified_samples(model, dataset, index_to_class,
figsize=(10, 10)):
    misclassified_images = []
    misclassified_labels = []
    misclassified_predictions = []

    # Iterate over dataset to collect misclassified images
```

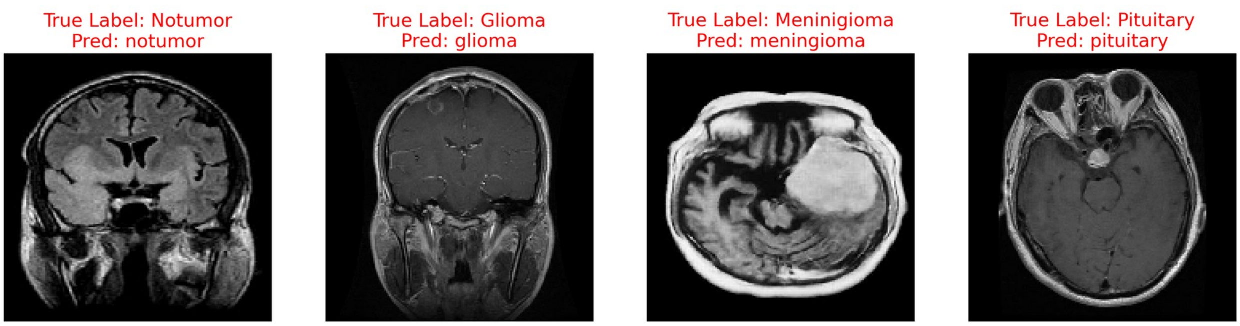
```python
    for image, true_label in dataset.unbatch():
        image_batch = tf.expand_dims(image, 0)
        predictions = model.predict(image_batch, verbose=False)
        predicted_label = np.argmax(predictions, axis=1)[0]
        true_class_index = np.argmax(true_label.numpy())

        if true_class_index != predicted_label:
            misclassified_images.append(image.numpy().squeeze())

misclassified_labels.append(index_to_class[true_class_index])

misclassified_predictions.append(index_to_class[predicted_label])

    # Determine number of rows and columns for subplot
    num_misclassified = len(misclassified_images)
    cols = int(np.sqrt(num_misclassified)) + 1
    rows = num_misclassified // cols + (num_misclassified % cols > 0)

    # Plotting misclassified images
    miss_classified_zip = zip(misclassified_images,
misclassified_labels, misclassified_predictions)
    plt.figure(figsize=figsize)
    for i, (image, true_label, predicted_label) in
enumerate(miss_classified_zip):
        plt.subplot(rows, cols, i + 1)
        plt.imshow(image, cmap='gray')
        plt.title(f"True: {true_label}\nPred: {predicted_label}",
color='red')
        plt.axis('off')

    plt.tight_layout()
    plt.show()

# Plotting misclassified images
plot_misclassified_samples(
    model=model,
    dataset=test_ds_preprocessed,
    index_to_class=inv_class_mappings,
    figsize=(10, 6)
)
```




```
# Function to load and preprocess an image
def load_and_preprocess_image(image_path, image_shape=(168, 168)):
    img = image.load_img(image_path, target_size=image_shape,
color_mode='grayscale')
    img_array = image.img_to_array(img) / 255.0
    img_array = np.expand_dims(img_array, axis=0)  # Add the batch
dimension
    return img_array

# Function to display a row of images with predictions
def display_images_and_predictions(image_paths, predictions,
true_labels, figsize=(20, 5)):
    plt.figure(figsize=figsize)
    for i, (image_path, prediction, true_label) in
enumerate(zip(image_paths, predictions, true_labels)):
        ax = plt.subplot(1, len(image_paths), i + 1)
        img_array = load_and_preprocess_image(image_path)
        img_array = np.squeeze(img_array)
        plt.imshow(img_array, cmap='gray')
        title_color = 'green' if prediction == true_label else 'red'
        plt.title(f'True Label: {true_label}\nPred: {prediction}',
color=title_color)
        plt.axis('off')
    plt.show()
```

```
# Load and preprocess the images from Validation directory
normal_image_path =
'/content/brain-tumor-mri-dataset/Validation/notumor/Te-no_0049.jpg'
glioma_image_path =
'/content/brain-tumor-mri-dataset/Validation/glioma/Te-gl_0069.jpg'
meningioma_image_path =
'/content/brain-tumor-mri-dataset/Validation/meningioma/Te-
me_0035.jpg'
pituitary_tumor_path =
'/content/brain-tumor-mri-dataset/Validation/pituitary/Te-pi_0028.jpg'

# Load and preprocess the images from Validation directory (LOCAL)
# normal_image_path = 'brain-tumor-mri-dataset/Validation/notumor/Te-
no_0049.jpg'
# glioma_image_path = 'brain-tumor-mri-dataset/Validation/glioma/Te-
gl_0069.jpg'
# meningioma_image_path =
'brain-tumor-mri-dataset/Validation/meningioma/Te-me_0035.jpg'
# pituitary_tumor_path =
'brain-tumor-mri-dataset/Validation/pituitary/Te-pi_0028.jpg'


# Image paths
image_paths = [
    normal_image_path,
    glioma_image_path,
    meningioma_image_path,
    pituitary_tumor_path
]

# True labels for images
true_labels = ['Notumor', 'Glioma', 'Meninigioma', 'Pituitary']

# Load and preprocess images, then make predictions
images = [load_and_preprocess_image(path) for path in image_paths]
predictions = [model.predict(image) for image in images]

# Determine the predicted labels
predicted_labels = [inv_class_mappings[np.argmax(one_hot)] for one_hot
in predictions]

# Output the predictions
print(f'Class Mappings: {class_mappings}')
print("\nNormal Image Prediction:", np.round(predictions[0], 3)[0])
print("Glioma Image Prediction:", np.round(predictions[1], 3)[0])
print("Meningioma Image Prediction:", np.round(predictions[2], 3)[0])
print("Pituitary Image Prediction:", np.round(predictions[3], 3)[0])

# Display images with predictions
```

```
display_images_and_predictions(image_paths, predicted_labels,
true_labels)

1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 35ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 30ms/step
Class Mappings: {'glioma': 0, 'meningioma': 1, 'notumor': 2,
'pituitary': 3}

Normal Image Prediction: [0.    0.001 0.999 0.   ]
Glioma Image Prediction: [1. 0. 0. 0.]
Meningioma Image Prediction: [0. 1. 0. 0.]
Pituitary Image Prediction: [0. 0. 0. 1.]
```




```
!pip install streamlit -q

━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 44.3/44.3 kB 2.6 MB/s eta
0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 9.9/9.9 MB 90.4 MB/s eta
0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 6.9/6.9 MB 123.5 MB/s eta
0:00:00
━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 79.1/79.1 kB 7.5 MB/s eta
0:00:00

%%writefile app.py
import streamlit as st
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import load_model
from tensorflow.keras.preprocessing import image
import time
import os

# --- Page Configuration ---
st.set_page_config(page_title="Brain MRI Tumor Classifier",
layout="centered")
```

```
# --- Define Class Mappings ---
class_mappings = {'Glioma': 0, 'Meninigioma': 1, 'Notumor': 2,
'Pituitary': 3}
inv_class_mappings = {v: k for k, v in class_mappings.items()}
class_emojis = {
    'Glioma': "□□",
    'Meninigioma': "□□",
    'Notumor': "□□",
    'Pituitary': "□□"
}
class_colors = {
    'Glioma': "#FF4B4B",
    'Meninigioma': "#FFD700",
    'Notumor': "#4CAF50",
    'Pituitary': "#9370DB"
}
image_dim = (168, 168)

# --- Load Model ---
model_path = 'model.keras'

@st.cache_resource
def load_brain_tumor_model(model_path):
    if not os.path.exists(model_path):
        st.error(f"Model file not found at {model_path}. Please ensure
the model file exists.")
        return None
    try:
        model = load_model(model_path)
        return model
    except Exception as e:
        st.error(f"Error loading model: {e}")
        return None

model = load_brain_tumor_model(model_path)
if model is None:
    st.stop()

# --- Image Preprocessing ---
def load_and_preprocess_image(uploaded_file, image_shape=(168, 168)):
    try:
        img = image.load_img(uploaded_file, target_size=image_shape,
color_mode='grayscale')
        img_array = image.img_to_array(img) / 255.0
        img_array = np.expand_dims(img_array, axis=0)
        return img_array
    except Exception as e:
        st.error(f"Error processing image: {e}")
        return None
```

```
# --- App Title ---
st.title("□ Brain MRI Tumor Classifier")
st.markdown("Upload a Brain MRI image to classify the type of tumor or verify if it's healthy.")

# --- Upload Image ---
uploaded_file = st.file_uploader("□ Upload an MRI image", type=["jpg", "jpeg", "png"])

if uploaded_file:
    st.image(uploaded_file, caption=" Uploaded Image", use_container_width=True)
    img_array = load_and_preprocess_image(uploaded_file, image_shape=image_dim)

    if img_array is not None:
        st.subheader("□ Classification Progress")
        progress_bar = st.progress(0)
        status_text = st.empty()

        for percent in range(0, 101, 10):
            time.sleep(0.05)
            progress_bar.progress(percent)
            status_text.text(f"Processing: {percent}%")

        predictions = model.predict(img_array)
        predicted_label_index = np.argmax(predictions, axis=1)[0]
        predicted_class = inv_class_mappings[predicted_label_index]
        confidence_scores = predictions[0]

        # --- Prediction Output ---
        st.markdown(f"""
        <div style='text-align: center; font-size: 1.5em; font-weight: bold; color: {class_colors[predicted_class]};'>
            Prediction: {class_emojis[predicted_class]} <br> {predicted_class}
        </div>
        """, unsafe_allow_html=True)

        # --- Confidence Scores ---
        st.subheader("□ Confidence Scores")
        for class_name, score in zip(class_mappings.keys(), confidence_scores):
            bar_percent = int(score * 100)
            st.markdown(f"""
                <div style='margin-bottom: 8px;'>
                    <b>{class_emojis[class_name]} {class_name}:</b> {bar_percent:.2f}%
                    <div style='background-color: #eee; border-radius: 4px; height: 15px;'>
```

```
                        <div style='width: {bar_percent}%; background-color: {class_colors[class_name]}; height: 100%; border-radius: 4px;'></div>
                    </div>
                </div>
            """, unsafe_allow_html=True)

# --- Footer and Credits ---
st.markdown("<br><hr style='margin-top: 30px; margin-bottom: 30px;'><br>", unsafe_allow_html=True)

st.markdown(
    """
    <div style='text-align: center; color: #4A4A4A; font-size: 0.9em;'>
        <p>Developed by: <b>Edwin P. Bayog Jr.</b><br>
        <i>BSCpE 3-A</i></p>
        <p style='margin-top: 5px;'>Course: <b>CpETE1 Embedded System 1 - Realtime Systems</b></p><br>
        <i>Technological University of the Philippines - Visayas</i>
    </div>
    <br>
    """,
    unsafe_allow_html=True
)
```

```
Writing app.py
```

# 8. Running the Project with Streamlit

```
# RUN IF YOU ARE IN COLAB
!wget -q -O - ipv4.icanhazip.com
print("Above is your Colab's public IP address, use as Tunnel Password.")

print("Starting Streamlit app in the background...")
!nohup streamlit run app.py --server.port 8501 --server.headless true --server.enableCORS false > streamlit.log &

import time
time.sleep(5)

print("Attempting to start localtunnel...")
!npx localtunnel --port 8501
```

```
34.125.90.56
Above is your Colab's public IP address, use as Tunnel Password.
Starting Streamlit app in the background...
nohup: redirecting stderr to stdout
Attempting to start localtunnel...
```

```
# RUN IF YOU ARE IN LOCAL JUPYTER NOTEBOOK
!streamlit run app.py & npx localtunnel --port 8501
```