Notebook

June 20, 2025

1 Brain Tumor Classification with a Convolutional Neural Network

1.1 1. Import Necessary Libraries

[52]:
```
import tensorflow as tf
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
import visualkeras
import os
import random
import warnings
warnings.filterwarnings("ignore")
```

1.2 2. Set Global Parameters

[4]:
```
# Model Training
IMAGE_SIZE = (150, 150)
BATCH_SIZE = 32
EPOCHS = 40
NUM_CLASSES = 4

# Setting seed for consistent results
SEED = 42
tf.keras.utils.set_random_seed(SEED)
tf.random.set_seed(SEED)
np.random.seed(SEED)
```

1.3 3. Load and Preprocess Data

[7]:
```
# Load Training and Testing Data
os.environ['DATA_PATH'] = './data'
train_dir = os.path.join(os.environ['DATA_PATH'], 'Training')
test_dir = os.path.join(os.environ['DATA_PATH'], 'Testing')
```

[54]:

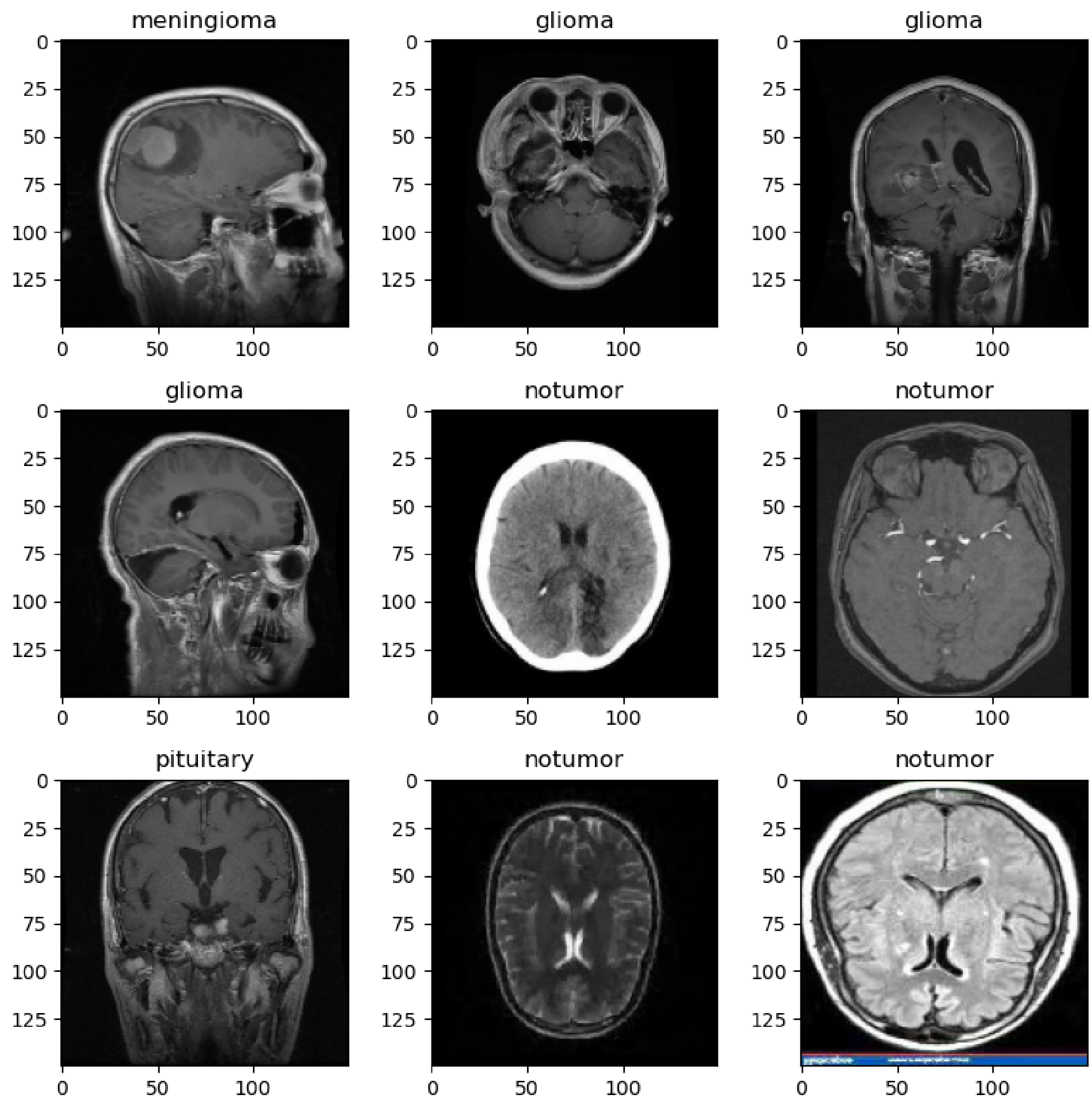
```python
# Preprocess Data
train_ds = tf.keras.utils.image_dataset_from_directory(
        train_dir,
        validation_split=0.2,
        subset="training",
        seed=SEED,
        image_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        label_mode='categorical'
    )

val_ds = tf.keras.utils.image_dataset_from_directory(
        train_dir,
        validation_split=0.2,
        subset="validation",
        seed=SEED,
        image_size=IMAGE_SIZE,
        batch_size=BATCH_SIZE,
        label_mode='categorical'
    )

test_ds = tf.keras.utils.image_dataset_from_directory(
        test_dir,
        seed=SEED,
        image_size=IMAGE_SIZE,
        batch_size=16,
        label_mode='categorical'
    )

# Pull Class Names for Sample Images/Visualizations
class_names = train_ds.class_names

def normalize(image, label):

        # Convert to float32 and normalize
        image = tf.cast(image, tf.float32) / 255.0

        return image, label

# Apply Normalization
train_ds = train_ds.map(normalize, num_parallel_calls=tf.data.AUTOTUNE)
val_ds = val_ds.map(normalize, num_parallel_calls=tf.data.AUTOTUNE)
test_ds = test_ds.map(normalize, num_parallel_calls=tf.data.AUTOTUNE)
```

```
Found 5712 files belonging to 4 classes.
Using 4570 files for training.
Found 5712 files belonging to 4 classes.
Using 1142 files for validation.
```

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

[11]:

```python
imgs, labs = next(iter(test_ds))
label_ids = np.argmax(labs, axis=1)

# Sample Images
plt.figure(figsize=(8,8))
for i in range(9):
    ax = plt.subplot(3,3,i+1)
    plt.imshow(imgs[i].numpy())
    plt.title(class_names[label_ids[i]])
    plt.axis("on")
plt.tight_layout()
plt.show()
```



1.4 4. Build Model

[14]:
```
model = tf.keras.Sequential([

        # Input layer
        tf.keras.layers.Input(shape=(IMAGE_SIZE[0], IMAGE_SIZE[1], 3)),

        # Convolutional layer 1
        tf.keras.layers.Conv2D(32, (4, 4), activation="relu"),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPooling2D(pool_size=(3, 3)),
        tf.keras.layers.Dropout(0.25),

        # Convolutional layer 2
        tf.keras.layers.Conv2D(64, (4, 4), activation="relu"),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPooling2D(pool_size=(3, 3)),
        tf.keras.layers.Dropout(0.25),

        # Convolutional layer 3
        tf.keras.layers.Conv2D(128, (4, 4), activation="relu"),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.MaxPooling2D(pool_size=(3, 3)),
        tf.keras.layers.Dropout(0.25),

        # Convolutional layer 4
        tf.keras.layers.Conv2D(128, (4, 4), activation="relu"),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Flatten(),
        tf.keras.layers.Dropout(0.4),

        # Full connect layers
        tf.keras.layers.Dense(512, activation="relu",
                              kernel_regularizer=tf.keras.regularizers.l2(0.01)),
        tf.keras.layers.BatchNormalization(),
        tf.keras.layers.Dropout(0.5),
        tf.keras.layers.Dense(NUM_CLASSES, activation="softmax")
    ])
```

[16]:
```
# Model Compilation
model.compile(
    optimizer=tf.keras.optimizers.Adam(
        learning_rate=0.0005,
        beta_1=0.9,
        beta_2=0.999
```

```
    ),
    loss='categorical_crossentropy',
    metrics=['accuracy', tf.keras.metrics.AUC(name='auc'), 'precision',␣
 ↪'recall']
)

model.summary()
```

```
Model: "sequential"
```

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 147, 147, 32)	1,568
batch_normalization (BatchNormalization)	(None, 147, 147, 32)	128
max_pooling2d (MaxPooling2D)	(None, 49, 49, 32)	0
dropout (Dropout)	(None, 49, 49, 32)	0
conv2d_1 (Conv2D)	(None, 46, 46, 64)	32,832
batch_normalization_1 (BatchNormalization)	(None, 46, 46, 64)	256
max_pooling2d_1 (MaxPooling2D)	(None, 15, 15, 64)	0
dropout_1 (Dropout)	(None, 15, 15, 64)	0
conv2d_2 (Conv2D)	(None, 12, 12, 128)	131,200
batch_normalization_2 (BatchNormalization)	(None, 12, 12, 128)	512
max_pooling2d_2 (MaxPooling2D)	(None, 4, 4, 128)	0
dropout_2 (Dropout)	(None, 4, 4, 128)	0
conv2d_3 (Conv2D)	(None, 1, 1, 128)	262,272
batch_normalization_3 (BatchNormalization)	(None, 1, 1, 128)	512
flatten (Flatten)	(None, 128)	0

```
dropout_3 (Dropout)             (None, 128)                    0

dense (Dense)                   (None, 512)               66,048

batch_normalization_4           (None, 512)                2,048
(BatchNormalization)

dropout_4 (Dropout)             (None, 512)                    0

dense_1 (Dense)                 (None, 4)                  2,052
```

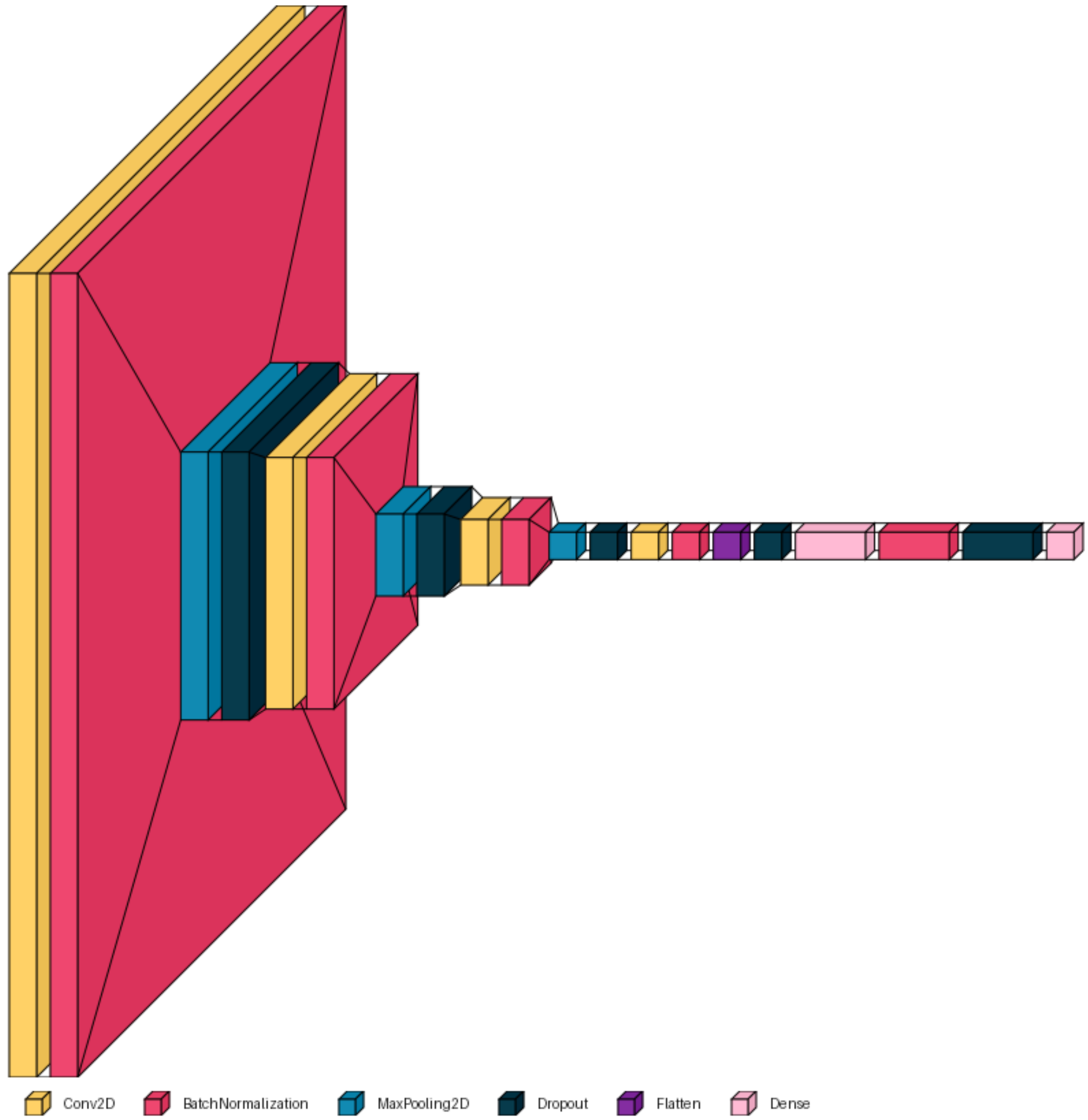
Total params: 499,428 (1.91 MB)

Trainable params: 497,700 (1.90 MB)

Non-trainable params: 1,728 (6.75 KB)

[18]:
```python
# Visualize Model
visualkeras.layered_view(model, to_file='model_viz.png', legend=True)
```

[18]:



1.5 5. Train Model

[21]:
```
# Create Callbacks
callbacks = [
    # Early Stopping
    tf.keras.callbacks.EarlyStopping(
        monitor='val_loss',
        min_delta=1e-4,
        patience=5,
        verbose=1,
        restore_best_weights=True
    ),
```

```python
    # Learning Rate Reduction
    tf.keras.callbacks.ReduceLROnPlateau(
        monitor='val_loss',
        factor=0.5,
        patience=5,
        min_lr=1e-6,

    )
]

# Train Model
history = model.fit(
    train_ds,
    validation_data=val_ds,
    epochs=EPOCHS,
    callbacks=callbacks
)
```

```
Epoch 1/40
143/143                28s 172ms/step -
accuracy: 0.4932 - auc: 0.7530 - loss: 3.3965 - precision: 0.5230 - recall:
0.4419 - val_accuracy: 0.4335 - val_auc: 0.5983 - val_loss: 4.2873 -
val_precision: 0.4422 - val_recall: 0.4291 - learning_rate: 5.0000e-04
Epoch 2/40
143/143                24s 167ms/step -
accuracy: 0.7125 - auc: 0.9052 - loss: 2.4002 - precision: 0.7354 - recall:
0.6754 - val_accuracy: 0.2644 - val_auc: 0.5665 - val_loss: 5.1575 -
val_precision: 0.2673 - val_recall: 0.2644 - learning_rate: 5.0000e-04
Epoch 3/40
143/143                24s 168ms/step -
accuracy: 0.7661 - auc: 0.9372 - loss: 1.9236 - precision: 0.7871 - recall:
0.7359 - val_accuracy: 0.5342 - val_auc: 0.7944 - val_loss: 2.6120 -
val_precision: 0.5536 - val_recall: 0.4974 - learning_rate: 5.0000e-04
Epoch 4/40
143/143                24s 167ms/step -
accuracy: 0.7858 - auc: 0.9483 - loss: 1.6173 - precision: 0.8042 - recall:
0.7643 - val_accuracy: 0.5902 - val_auc: 0.8236 - val_loss: 2.4681 -
val_precision: 0.6000 - val_recall: 0.5779 - learning_rate: 5.0000e-04
Epoch 5/40
143/143                24s 168ms/step -
accuracy: 0.8081 - auc: 0.9549 - loss: 1.3759 - precision: 0.8221 - recall:
0.7865 - val_accuracy: 0.7285 - val_auc: 0.9136 - val_loss: 1.5879 -
val_precision: 0.7377 - val_recall: 0.7119 - learning_rate: 5.0000e-04
Epoch 6/40
143/143                24s 168ms/step -
accuracy: 0.8272 - auc: 0.9609 - loss: 1.1838 - precision: 0.8423 - recall:
0.8107 - val_accuracy: 0.8039 - val_auc: 0.9529 - val_loss: 1.1597 -
```

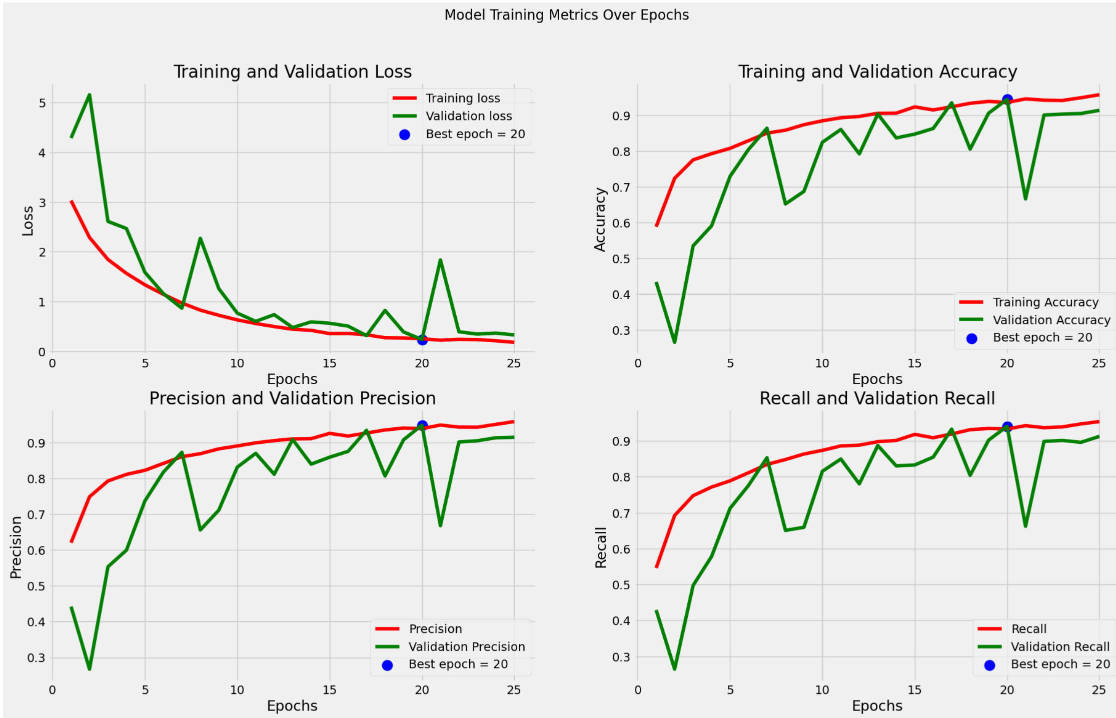
```
val_precision: 0.8181 - val_recall: 0.7758 - learning_rate: 5.0000e-04
Epoch 7/40
143/143            24s 167ms/step -
accuracy: 0.8474 - auc: 0.9691 - loss: 0.9960 - precision: 0.8614 - recall:
0.8320 - val_accuracy: 0.8634 - val_auc: 0.9764 - val_loss: 0.8669 -
val_precision: 0.8735 - val_recall: 0.8529 - learning_rate: 5.0000e-04
Epoch 8/40
143/143            24s 167ms/step -
accuracy: 0.8474 - auc: 0.9704 - loss: 0.8911 - precision: 0.8591 - recall:
0.8384 - val_accuracy: 0.6515 - val_auc: 0.8394 - val_loss: 2.2720 -
val_precision: 0.6564 - val_recall: 0.6506 - learning_rate: 5.0000e-04
Epoch 9/40
143/143            24s 170ms/step -
accuracy: 0.8722 - auc: 0.9783 - loss: 0.7379 - precision: 0.8824 - recall:
0.8623 - val_accuracy: 0.6865 - val_auc: 0.8922 - val_loss: 1.2605 -
val_precision: 0.7117 - val_recall: 0.6594 - learning_rate: 5.0000e-04
Epoch 10/40
143/143            24s 167ms/step -
accuracy: 0.8805 - auc: 0.9797 - loss: 0.6587 - precision: 0.8889 - recall:
0.8710 - val_accuracy: 0.8240 - val_auc: 0.9682 - val_loss: 0.7687 -
val_precision: 0.8320 - val_recall: 0.8152 - learning_rate: 5.0000e-04
Epoch 11/40
143/143            24s 167ms/step -
accuracy: 0.8914 - auc: 0.9841 - loss: 0.5647 - precision: 0.8987 - recall:
0.8833 - val_accuracy: 0.8599 - val_auc: 0.9760 - val_loss: 0.6017 -
val_precision: 0.8707 - val_recall: 0.8494 - learning_rate: 5.0000e-04
Epoch 12/40
143/143            24s 166ms/step -
accuracy: 0.8975 - auc: 0.9861 - loss: 0.4997 - precision: 0.9075 - recall:
0.8904 - val_accuracy: 0.7916 - val_auc: 0.9551 - val_loss: 0.7371 -
val_precision: 0.8122 - val_recall: 0.7802 - learning_rate: 5.0000e-04
Epoch 13/40
143/143            24s 167ms/step -
accuracy: 0.8973 - auc: 0.9864 - loss: 0.4678 - precision: 0.9042 - recall:
0.8909 - val_accuracy: 0.9028 - val_auc: 0.9825 - val_loss: 0.4780 -
val_precision: 0.9093 - val_recall: 0.8870 - learning_rate: 5.0000e-04
Epoch 14/40
143/143            24s 166ms/step -
accuracy: 0.9074 - auc: 0.9880 - loss: 0.4146 - precision: 0.9127 - recall:
0.9037 - val_accuracy: 0.8363 - val_auc: 0.9695 - val_loss: 0.5919 -
val_precision: 0.8404 - val_recall: 0.8301 - learning_rate: 5.0000e-04
Epoch 15/40
143/143            24s 167ms/step -
accuracy: 0.9257 - auc: 0.9906 - loss: 0.3584 - precision: 0.9285 - recall:
0.9198 - val_accuracy: 0.8468 - val_auc: 0.9721 - val_loss: 0.5647 -
val_precision: 0.8599 - val_recall: 0.8327 - learning_rate: 5.0000e-04
Epoch 16/40
143/143            24s 166ms/step -
```

```
accuracy: 0.9095 - auc: 0.9886 - loss: 0.3697 - precision: 0.9120 - recall:
0.9031 - val_accuracy: 0.8625 - val_auc: 0.9735 - val_loss: 0.5069 -
val_precision: 0.8761 - val_recall: 0.8546 - learning_rate: 5.0000e-04
Epoch 17/40
143/143            24s 167ms/step -
accuracy: 0.9231 - auc: 0.9889 - loss: 0.3413 - precision: 0.9276 - recall:
0.9181 - val_accuracy: 0.9343 - val_auc: 0.9905 - val_loss: 0.3148 -
val_precision: 0.9350 - val_recall: 0.9326 - learning_rate: 5.0000e-04
Epoch 18/40
143/143            24s 166ms/step -
accuracy: 0.9326 - auc: 0.9940 - loss: 0.2750 - precision: 0.9354 - recall:
0.9304 - val_accuracy: 0.8047 - val_auc: 0.9516 - val_loss: 0.8220 -
val_precision: 0.8074 - val_recall: 0.8039 - learning_rate: 5.0000e-04
Epoch 19/40
143/143            24s 167ms/step -
accuracy: 0.9387 - auc: 0.9932 - loss: 0.2682 - precision: 0.9416 - recall:
0.9347 - val_accuracy: 0.9054 - val_auc: 0.9839 - val_loss: 0.3901 -
val_precision: 0.9083 - val_recall: 0.9019 - learning_rate: 5.0000e-04
Epoch 20/40
143/143            24s 167ms/step -
accuracy: 0.9344 - auc: 0.9931 - loss: 0.2628 - precision: 0.9389 - recall:
0.9310 - val_accuracy: 0.9440 - val_auc: 0.9949 - val_loss: 0.2379 -
val_precision: 0.9496 - val_recall: 0.9405 - learning_rate: 5.0000e-04
Epoch 21/40
143/143            24s 168ms/step -
accuracy: 0.9471 - auc: 0.9957 - loss: 0.2216 - precision: 0.9505 - recall:
0.9442 - val_accuracy: 0.6655 - val_auc: 0.8529 - val_loss: 1.8379 -
val_precision: 0.6684 - val_recall: 0.6620 - learning_rate: 5.0000e-04
Epoch 22/40
143/143            24s 167ms/step -
accuracy: 0.9413 - auc: 0.9933 - loss: 0.2475 - precision: 0.9426 - recall:
0.9366 - val_accuracy: 0.9002 - val_auc: 0.9828 - val_loss: 0.3930 -
val_precision: 0.9024 - val_recall: 0.8984 - learning_rate: 5.0000e-04
Epoch 23/40
143/143            24s 167ms/step -
accuracy: 0.9374 - auc: 0.9926 - loss: 0.2501 - precision: 0.9399 - recall:
0.9341 - val_accuracy: 0.9028 - val_auc: 0.9861 - val_loss: 0.3467 -
val_precision: 0.9058 - val_recall: 0.9011 - learning_rate: 5.0000e-04
Epoch 24/40
143/143            24s 167ms/step -
accuracy: 0.9499 - auc: 0.9954 - loss: 0.2074 - precision: 0.9530 - recall:
0.9486 - val_accuracy: 0.9046 - val_auc: 0.9838 - val_loss: 0.3666 -
val_precision: 0.9142 - val_recall: 0.8958 - learning_rate: 5.0000e-04
Epoch 25/40
143/143            24s 168ms/step -
accuracy: 0.9492 - auc: 0.9957 - loss: 0.1978 - precision: 0.9510 - recall:
0.9461 - val_accuracy: 0.9133 - val_auc: 0.9857 - val_loss: 0.3296 -
val_precision: 0.9156 - val_recall: 0.9124 - learning_rate: 5.0000e-04
```

```
Epoch 25: early stopping
Restoring model weights from the end of the best epoch: 20.
```

[29]:
```
# Visualize Training Performance
train_acc = history.history['accuracy']
train_loss = history.history['loss']
train_pre = history.history['precision']
train_recall = history.history['recall']
val_acc = history.history['val_accuracy']
val_loss = history.history['val_loss']
val_per = history.history['val_precision']
val_recall = history.history['val_recall']

index_loss = np.argmin(val_loss)
val_lowest = val_loss[index_loss]
index_acc = np.argmax(val_acc)
acc_highest = val_acc[index_acc]
index_precision = np.argmax(val_per)
per_highest = val_per[index_precision]
index_recall = np.argmax(val_recall)
recall_highest = val_recall[index_recall]

Epochs = [i + 1 for i in range(len(train_acc))]
loss_label = f'Best epoch = {str(index_loss + 1)}'
acc_label = f'Best epoch = {str(index_acc + 1)}'
per_label = f'Best epoch = {str(index_precision + 1)}'
recall_label = f'Best epoch = {str(index_recall + 1)}'


plt.figure(figsize=(20, 12))
plt.style.use('fivethirtyeight')


plt.subplot(2, 2, 1)
plt.plot(Epochs, train_loss, 'r', label='Training loss')
plt.plot(Epochs, val_loss, 'g', label='Validation loss')
plt.scatter(index_loss + 1, val_lowest, s=150, c='blue', label=loss_label)
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid(True)

plt.subplot(2, 2, 2)
plt.plot(Epochs, train_acc, 'r', label='Training Accuracy')
plt.plot(Epochs, val_acc, 'g', label='Validation Accuracy')
plt.scatter(index_acc + 1, acc_highest, s=150, c='blue', label=acc_label)
```

```
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.grid(True)

plt.subplot(2, 2, 3)
plt.plot(Epochs, train_pre, 'r', label='Precision')
plt.plot(Epochs, val_per, 'g', label='Validation Precision')
plt.scatter(index_precision + 1, per_highest, s=150, c='blue', label=per_label)
plt.title('Precision and Validation Precision')
plt.xlabel('Epochs')
plt.ylabel('Precision')
plt.legend()
plt.grid(True)

plt.subplot(2, 2, 4)
plt.plot(Epochs, train_recall, 'r', label='Recall')
plt.plot(Epochs, val_recall, 'g', label='Validation Recall')
plt.scatter(index_recall + 1, recall_highest, s=150, c='blue',␣
 ↪label=recall_label)
plt.title('Recall and Validation Recall')
plt.xlabel('Epochs')
plt.ylabel('Recall')
plt.legend()
plt.grid(True)

plt.suptitle('Model Training Metrics Over Epochs', fontsize=16)
plt.show()
```



1.6 6. Evaluate Model

[34]:
```
# Evaluate
train_score = model.evaluate(train_ds, verbose=1)
valid_score = model.evaluate(val_ds, verbose=1)
test_score = model.evaluate(test_ds, verbose=1)

print(f"Train Loss: {train_score[0]:.4f}")
print(f"Train Accuracy: {train_score[1]*100:.2f}%")
print('-' * 20)
print(f"Validation Loss: {valid_score[0]:.4f}")
print(f"Validation Accuracy: {valid_score[1]*100:.2f}%")
print('-' * 20)
print(f"Test Loss: {test_score[0]:.4f}")
print(f"Test Accuracy: {test_score[1]*100:.2f}%")
```

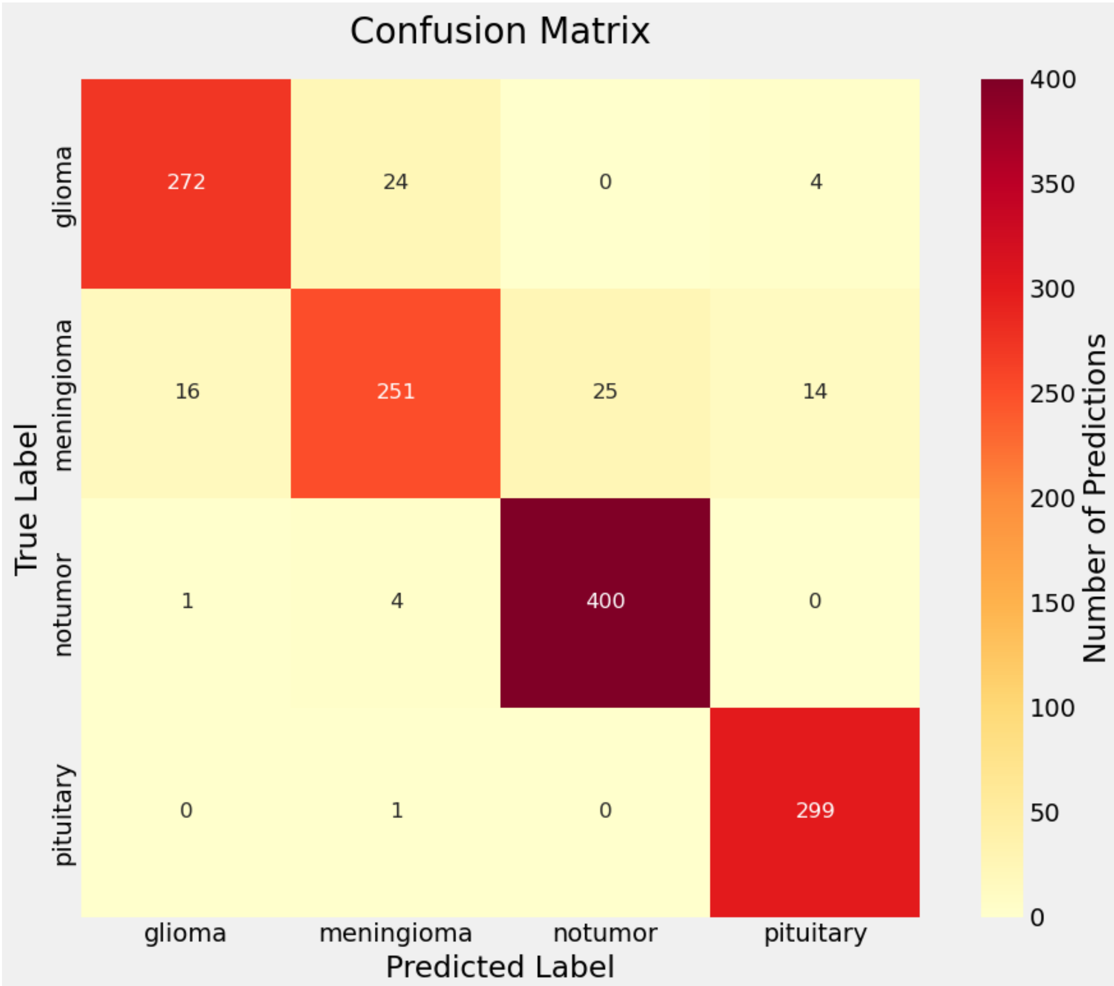
```
143/143              5s 31ms/step -
accuracy: 0.9785 - auc: 0.9992 - loss: 0.1493 - precision: 0.9796 - recall:
0.9767
36/36              1s 31ms/step -
accuracy: 0.9519 - auc: 0.9960 - loss: 0.2237 - precision: 0.9562 - recall:
0.9502
82/82              1s 17ms/step -
accuracy: 0.9224 - auc: 0.9929 - loss: 0.2747 - precision: 0.9286 - recall:
0.9158
```

```
Train Loss: 0.1466
Train Accuracy: 98.10%
--------------------
Validation Loss: 0.2379
Validation Accuracy: 94.40%
--------------------
Test Loss: 0.2548
Test Accuracy: 93.21%
```

[58]:

```python
# Get predictions and true labels
y_pred = []
y_true = []

# Iterate through the dataset
for images, labels in test_ds:
    # Get predictions for this batch
    predictions = model.predict(images, verbose=0)
    # Convert predictions and labels to class indices
    pred_indices = np.argmax(predictions, axis=1)
    true_indices = np.argmax(labels, axis=1)

    y_pred.extend(pred_indices)
    y_true.extend(true_indices)

y_pred = np.array(y_pred)
y_true = np.array(y_true)

# Create confusion matrix
cm = confusion_matrix(y_true, y_pred)

# Plot
plt.figure(figsize=(10, 8))
sns.heatmap(cm,
            annot=True,
            fmt='d',
            xticklabels=class_names,
            yticklabels=class_names,
            cmap='YlOrRd',
            cbar_kws={'label': 'Number of Predictions'},
            annot_kws={'size': 12},
            square=True)

plt.title('Confusion Matrix', pad=20)
plt.ylabel('True Label')
plt.xlabel('Predicted Label')

# Adjust layout to prevent label cutoff
```

```
plt.tight_layout()
```



[60]:
```
# Print Classification Report
print(classification_report(y_true, y_pred, target_names=class_names))
```

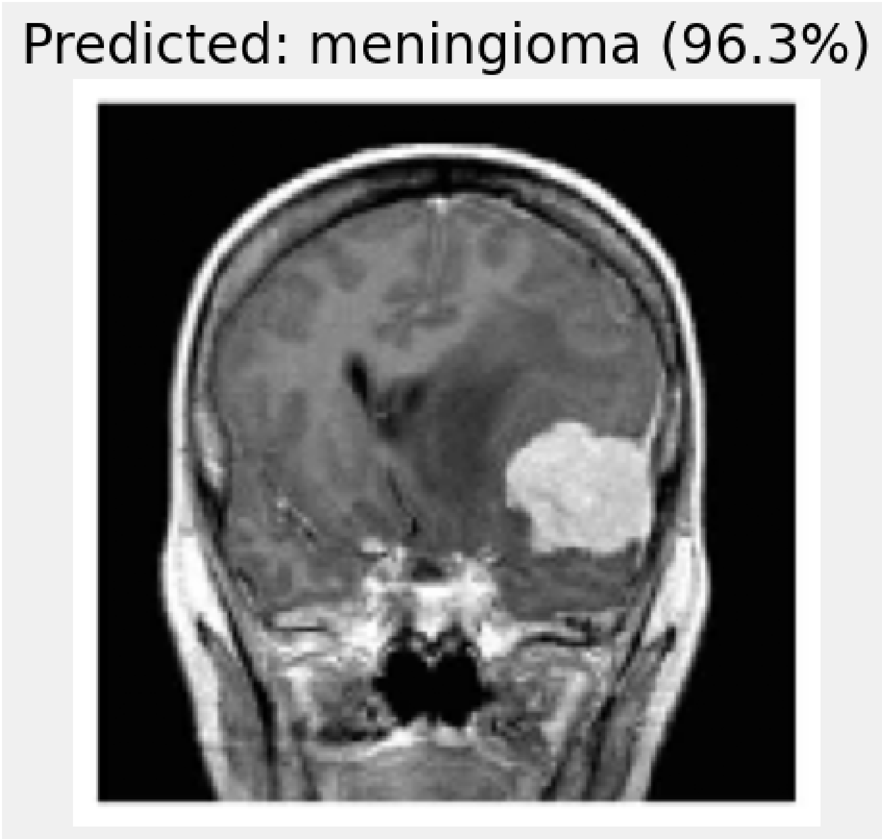
```
              precision    recall  f1-score   support

      glioma       0.94      0.91      0.92       300
  meningioma       0.90      0.82      0.86       306
     notumor       0.94      0.99      0.96       405
   pituitary       0.94      1.00      0.97       300

    accuracy                           0.93      1311
   macro avg       0.93      0.93      0.93      1311
weighted avg       0.93      0.93      0.93      1311
```

1.7 7. Test Model

[98]:
```python
# Make a Prediction
def predict_image(model, img_path, image_size, class_names):
    # Load & resize
    img = tf.keras.utils.load_img(img_path, target_size=image_size)

    # Convert to array & normalize to [0,1]
    img_array = tf.keras.utils.img_to_array(img) / 255.0

    # Add batch dimension
    img_batch = np.expand_dims(img_array, axis=0)

    # Run model
    preds = model.predict(img_batch)
    pred_idx = np.argmax(preds[0])
    pred_label = class_names[pred_idx]
    confidence = preds[0][pred_idx]

    return img_array, pred_label, confidence
```

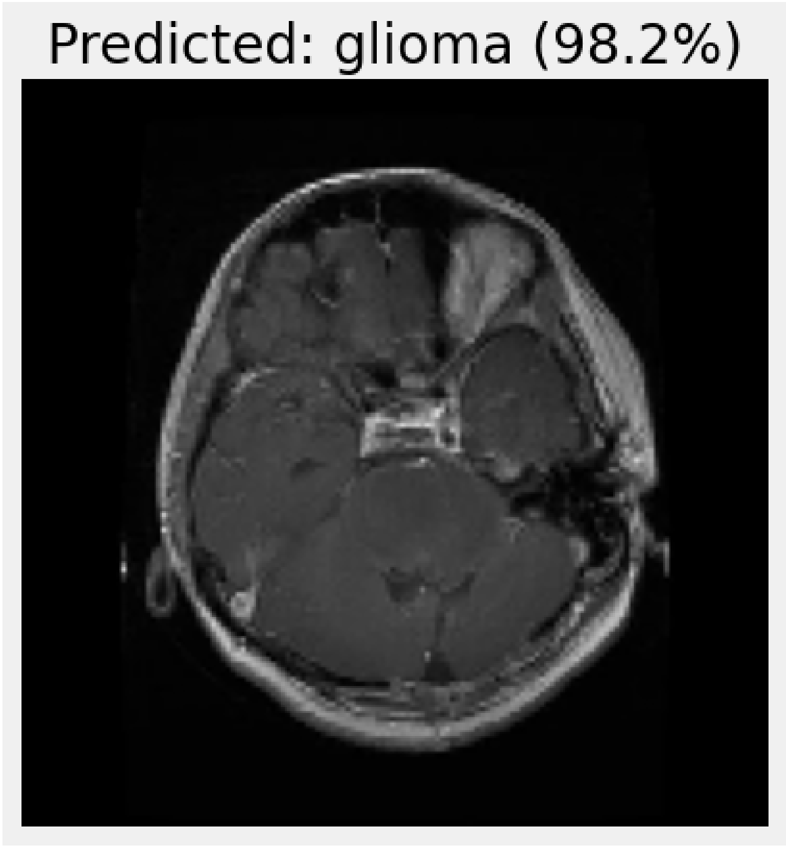
[90]:
```python
# Test
img_path = './data/Testing/meningioma/Te-me_0014.jpg'
img, label, conf = predict_image(model, img_path, IMAGE_SIZE, class_names)

plt.imshow(img)
plt.title(f'Predicted: {label} ({conf:.1%})')
plt.axis('off')
plt.show()
```

```
1/1              0s 26ms/step
```



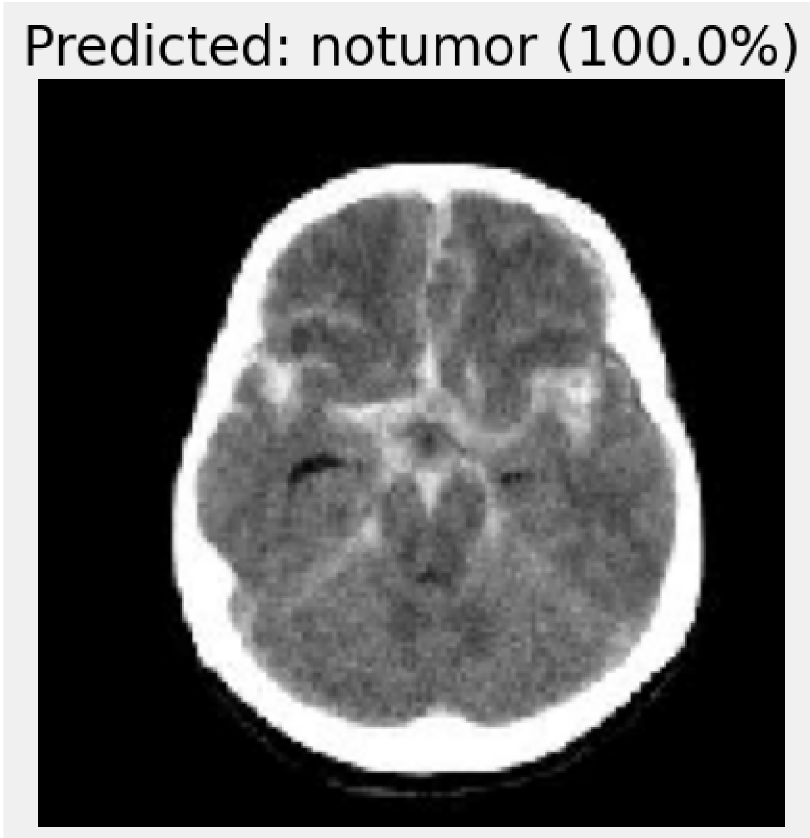
[92]:
```
img_path = './data/Testing/glioma/Te-gl_0010.jpg'
img, label, conf = predict_image(model, img_path, IMAGE_SIZE, class_names)

plt.imshow(img)
plt.title(f'Predicted: {label} ({conf:.1%})')
plt.axis('off')
plt.show()
```

```
1/1              0s 26ms/step
```



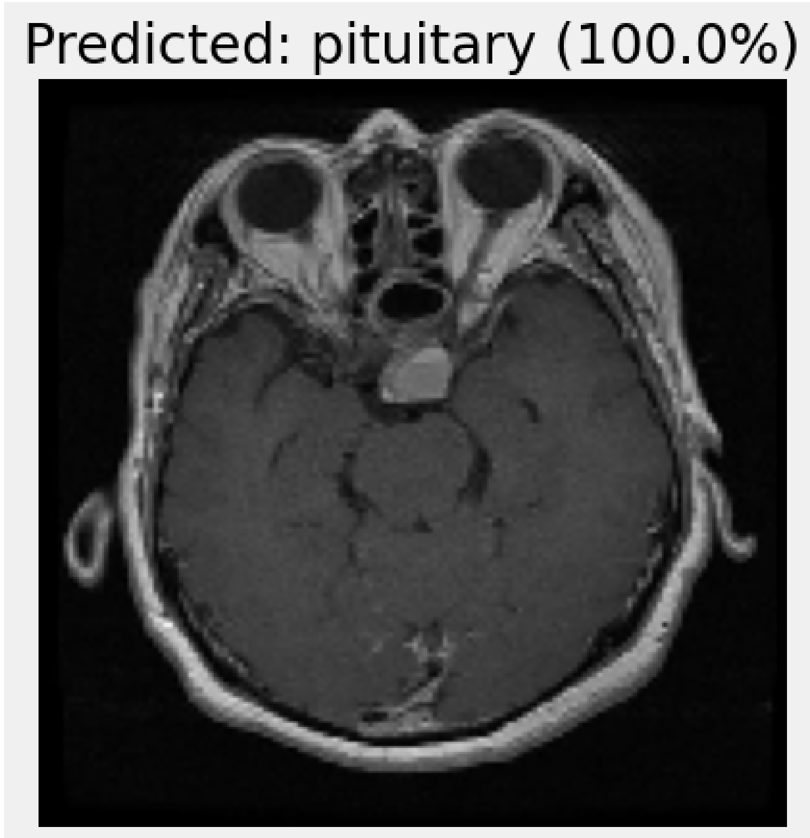
[94]:
```
img_path = './data/Testing/notumor/Te-no_0011.jpg'
img, label, conf = predict_image(model, img_path, IMAGE_SIZE, class_names)

plt.imshow(img)
plt.title(f'Predicted: {label} ({conf:.1%})')
plt.axis('off')
plt.show()
```

```
1/1               0s 26ms/step
```



[96]:
```
img_path = './data/Testing/pituitary/Te-pi_0027.jpg'
img, label, conf = predict_image(model, img_path, IMAGE_SIZE, class_names)

plt.imshow(img)
plt.title(f'Predicted: {label} ({conf:.1%})')
plt.axis('off')
plt.show()
```

```
1/1              0s 30ms/step
```



This notebook was converted with convert.ploomber.io