winters_2025_brain_tumor_cnn_clasification_v0.3

March 7, 2025

- Wiley Winters
- MSDS 686 Deep Learning
- Week 7-8 Kaggle Project — Brain Tumor Classification
- 2025-MAR-09

0.1 Requirements

0.1.1 Required for 80%

Complete project on *kaggle.com* using the skills learned in the Deep Learning class. The following are required: - Show/plot sample images or data with labels - Include at least one of the following - Convolution - Max Pooling - Batch Normalization - Dropout - LSTM - TF-IDf - Use validation data - Evaluate model on test data

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0.2 Additional for another 20%

- Use data augmentation
- Use at least one of the following:
  - Kernels
  - Activation functions
  - Loss functions
  - Libraries
  - Methods
- Learning rate optimization
- Functional API model
- Transfer learning with or without trainable parameters
- Confusion matrix and / or ROC plots
- Plots of accuracy/loss vs epochs
- Show/plot sample incorrect prediction with labels and correct label

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1.0 | Load Libraries and Packages

[1]:
```python
# General Imports
import numpy as np
```

```python
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import os, logging, random
from datetime import datetime

# Data prep and model scoring
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.metrics import classification_report

# TensorFlow likes to display a lot of debug information
# on my home system
# I will squash the messages
os.environ['TF_CPP_MIN_LOG_LEVEL'] = '3'
logging.getLogger('tensorFlow').setLevel(logging.FATAL)

# tensorflow and keras' API
import tensorflow as tf
from tensorflow import keras

# Model building
from tensorflow.keras import backend, optimizers, regularizers, models
from tensorflow.keras.layers import Dense, Dropout, Flatten
from tensorflow.keras.layers import Conv2D, MaxPooling2D, BatchNormalization
from tensorflow.keras.preprocessing.image import ImageDataGenerator

# Model architecture visualization
from visualkeras import layered_view

# Model training
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
from tensorflow.keras.metrics import Precision, Recall, AUC

# Make plots have guidelines
plt.style.use('ggplot')

# Squash Python warnings
import warnings
warnings.filterwarnings('ignore')
```

```
WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
E0000 00:00:1741353098.026237 1061755 cuda_dnn.cc:8310] Unable to register cuDNN
factory: Attempting to register factory for plugin cuDNN when one has already
been registered
E0000 00:00:1741353098.032022 1061755 cuda_blas.cc:1418] Unable to register
cuBLAS factory: Attempting to register factory for plugin cuBLAS when one has
```

already been registered

1.1 | Set Random Seed for Reproducibility

[2]:
```
tf.keras.utils.set_random_seed(42)
tf.random.set_seed(42)
np.random.seed(42)
random.seed(42)
```

1.2 | Declare Global Variables

[3]:
```
# Define training and testing image directories
home_dir = '/home/wiley'
trn_dir = home_dir+'/regis/dataScience/kaggleProject/images/data/training'
tst_dir = home_dir+'/regis/dataScience/kaggleProject/images/data/testing'

# Define classes
classes = ['negative', 'positive']

# Image size and shape
img_size = (224, 224)
img_shape = (224, 224, 3)

# Number of classes
num_classes = 2

# Declare batch size
batch_size = 64

# Flag to save weights
save = True
```

2.0 | Define Functions

2.1 | Load DataFrames - Join image filename and path information - Create labels from class directory names - Create dataframe - Randomize dataframe rows

[4]:
```
def load_dataframe(path):
    # Derive image file paths and labels from directory structure
    labels, paths = zip(*[(label, os.path.join(path, label, image))
                        for label in os.listdir(path)
                        if os.path.isdir(os.path.join(path, label))
                        for image in os.listdir(os.path.join(path, label))])

    # Create DataFrame
    df = pd.DataFrame({'paths': paths, 'labels': labels})

    # Randomize rows to help eliminate bias
```

```
    df = df.sample(frac=1, random_state=42).reset_index(drop=True)

    return df
```

2.2 | Plot Performance Metrics Plot the following: - Training loss - Validation loss - Training Accuracy - Validation Accuracy - Training Precision - Validation Precision - Training Recall - Validation Recall - Training AUC - Validation AUC

[5]:
```
def plot_history(history):
    epochs = range(1, len(history.history['accuracy']) + 1)

    # Plot training and validation loss
    plt.figure(figsize=(20,12))
    plt.subplot(2,2,1)
    plt.plot(epochs, history.history['loss'], 'b', label = 'Training Loss')
    plt.plot(epochs, history.history['val_loss'], 'r', label = 'Validation␣
↪Loss')
    plt.title('Training and Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()

    # Plot training and validation accuracy
    plt.subplot(2,2,2)
    plt.plot(epochs, history.history['accuracy'], 'b', label = 'Training␣
↪Accuracy')
    plt.plot(epochs, history.history['val_accuracy'], 'r', label = 'Validation␣
↪Accuracy')
    plt.title('Training and Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()

    plt.suptitle('Model Loss and Accuracy over Epochs', fontsize=16)
    plt.show()

    # Plot training and validation precision
    plt.figure(figsize=(20,12))
    plt.subplot(2,2,1)
    plt.plot(epochs, history.history['precision'], 'b', label='Training␣
↪Precision')
    plt.plot(epochs, history.history['val_precision'], 'r', label='Validation␣
↪Precision')
    plt.title('Training and Validation Precision')
    plt.xlabel('Epochs')
    plt.ylabel('Precision')
    plt.legend()
```

```python
    # Plot training and validation recall
    plt.subplot(2,2,2)
    plt.plot(epochs, history.history['recall'], 'b', label='Training Recall')
    plt.plot(epochs, history.history['val_recall'], 'r', label='Validation␣
↪Recall')
    plt.title('Training and Validation Recall')
    plt.xlabel('Epochs')
    plt.ylabel('Recall')
    plt.legend()

    plt.suptitle('Model Precision and Recall over Epochs', fontsize=16)
    plt.show()

    # Plot training and validation AUC
    plt.figure(figsize=(5,3))
    plt.plot(epochs, history.history['auc'], 'b', label='Training AUC')
    plt.plot(epochs, history.history['val_auc'], 'r', label='Validation AUC')
    plt.title('Training and Validation AUC')
    plt.xlabel('Epochs')
    plt.ylabel('Recall')
    plt.legend()
    plt.show()
```

2.3 | Evaluate Model's Performance on Test DataSet - Infer loss, accuracy, precision, recall, and AUC from dataset - Compute F1 Score from precision and recall

[6]:
```python
def score_model(model, ds):
    # Get metrics from test data
    loss, acc, auc, prec, recall = model.evaluate(ds)

    # Calculate F1 Score from precision and recall
    f1_score = 2 * (prec * recall) / (prec + recall)

    # Print results
    print('-' * 30)
    print(f'Loss:      {loss:.4f}')
    print(f'Accuracy:  {acc:.4f}')
    print(f'Precision: {prec:.4f}')
    print(f'Recall:    {recall:.4f}')
    print(f'AUC:       {auc:.4f}')
    print(f'F1 Score:  {f1_score:.4f}')
    print('-' * 30)
```

2.4 | Plot Confusion Matrix

[7]:
```python
def plot_cm(model, ds):
    # Get predictions from dataset
```

```
    preds = np.argmax(np.round(model.predict(ds)), axis=1)

    # Create confusion matrix
    cm = confusion_matrix(ds.classes, preds)

    # Visualize confusion matrix
    plt.figure(figsize=(5,3))
    sns.heatmap(cm, annot=True, fmt='d', cmap='viridis',
                xticklabels=classes,
                yticklabels=classes)
    plt.title('Confusion Matrix')
    plt.xlabel('Predicted')
    plt.ylabel('True')
    plt.show()
```

2.5 | Compute TPR and TNR

[8]:
```
def compute_tpr(model, ds):
    # get predictions from dataset
    preds = np.argmax(np.round(model.predict(ds)), axis=1)

    # Create confusion matrix
    cm = confusion_matrix(ds.classes, preds)

    # Extract required values from confusion matrix
    (tn, fp, fn, tp) = cm.flatten()

    # Calculate TPR
    tpr = tp / (tp + fn)

    # Calculate TNR
    tnr = tn / (tn + fp)

    # Print TPR and TNR
    print('-' * 30)
    print(f'True Positive Rate (TPR): {tpr:.4f}')
    print(f'True Negative Rate (TNR): {tnr:.4f}')
    print('-' * 30)
```

2.6 | Show True vs Predicted Labels

[9]:
```
def display_preds(model, ds):
    # Extract true and predicted labels from dataset
    images, labels = next(ds)
    preds = model.predict(images)
    pred_labs = np.argmax(preds, axis=1)
    dict = ds.class_indices
    tr_labels = list(dict.keys())
```

```
    # Plot the images with true and predicted labels
    plt.figure(figsize=(20,20))
    for i in range(16):
        img = images[i]
        label = labels[i]
        tr_label = classes[np.argmax(label)]
        pred_label = classes[pred_labs[i]]
        plt.subplot(4,4,i+1)
        plt.imshow(img)
        color = 'green' if tr_label == pred_label else 'red'
        plt.title('True:      %s \nPredict:  %s' % (tr_label, pred_label),␣
↪fontsize=15,
                  loc='left', color=color)
        plt.axis('off')

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

2.7 | Print Images

[10]:
```
def print_images(ds):
    # Pull images and labels out of the dataset
    images, labels = next(ds)

    # Create a dictionary of class indices
    dict = ds.class_indices

    # Form classes from the dictionary created in last step
    classes = list(dict.keys())

    # Plot the images and labels -- 16 images at a time
    plt.figure(figsize=(20,20))
    for i in range(16):
        img = images[i]
        label = labels[i]
        class_name = classes[np.argmax(label)]
        plt.subplot(4,4,i+1)
        plt.imshow(img)
        plt.title(class_name, loc='left', fontsize=15)
        plt.axis('off')

    plt.show()
```

3.0 | Load Data

3.1 | Create and Load DataFrame for EDA

```
[11]: # Load training data
trn_df = load_dataframe(trn_dir)

# Load testing data
tst_df = load_dataframe(tst_dir)

# Take a look at the results
print('Training:   \n', trn_df.head(10).to_markdown())
print('Testing:    \n', tst_df.head(10).to_markdown())
```

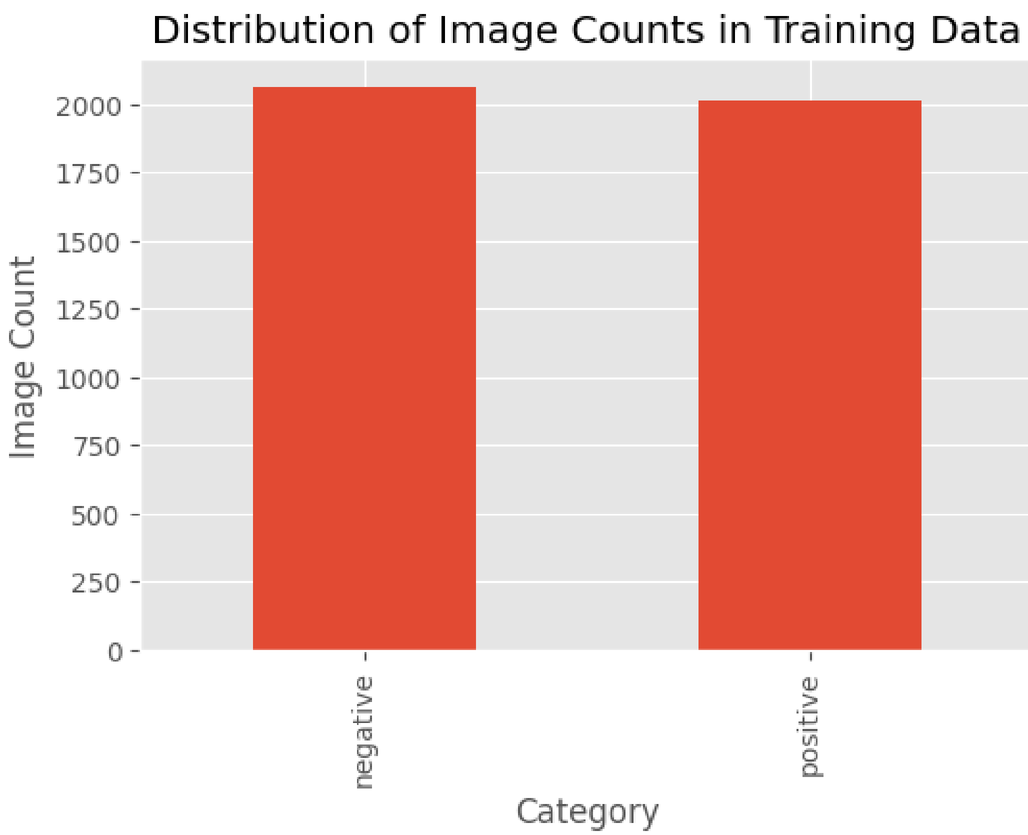
```
Training:
 |    | paths
| labels   |
|---:|:--------------------------------------------------------------------------
-------------------------|:---------|
|  0 | /home/wiley/regis/dataScience/kaggleProject/images/data/training/negative
/image(192).jpg          | negative |
|  1 | /home/wiley/regis/dataScience/kaggleProject/images/data/training/negative
/image(122).jpg          | negative |
|  2 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (769).jpg   | negative |
|  3 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (511).jpg   | negative |
|  4 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(720).jpg       | positive |
|  5 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (468).jpg   | negative |
|  6 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (1108).jpg | negative |
|  7 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (360).jpg   | negative |
|  8 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(402).jpg       | positive |
|  9 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (177).jpg   | negative |
Testing:
 |    | paths
| labels   |
|---:|:--------------------------------------------------------------------------
------------------------|:---------|
```

```
|  0 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/positive/Cancer
(1404).jpg      | positive |
|  1 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/negative/Not
Cancer  (1168).jpg | negative |
|  2 | /home/wiley/regis/dataScience/kaggleProject/images/data/testing/negative/
image(30).jpg          | negative |
|  3 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/negative/Not
Cancer  (720).jpg  | negative |
|  4 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/positive/Cancer
(1559).jpg      | positive |
|  5 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/positive/Cancer
(2272).jpg      | positive |
|  6 | /home/wiley/regis/dataScience/kaggleProject/images/data/testing/negative/
image(33).jpg          | negative |
|  7 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/positive/Cancer
(714).jpg       | positive |
|  8 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/negative/Not
Cancer  (1090).jpg | negative |
|  9 |
/home/wiley/regis/dataScience/kaggleProject/images/data/testing/positive/Cancer
(300).jpg       | positive |
```

4.0 | EDA

4.1 | Look at Training Images' Distribution

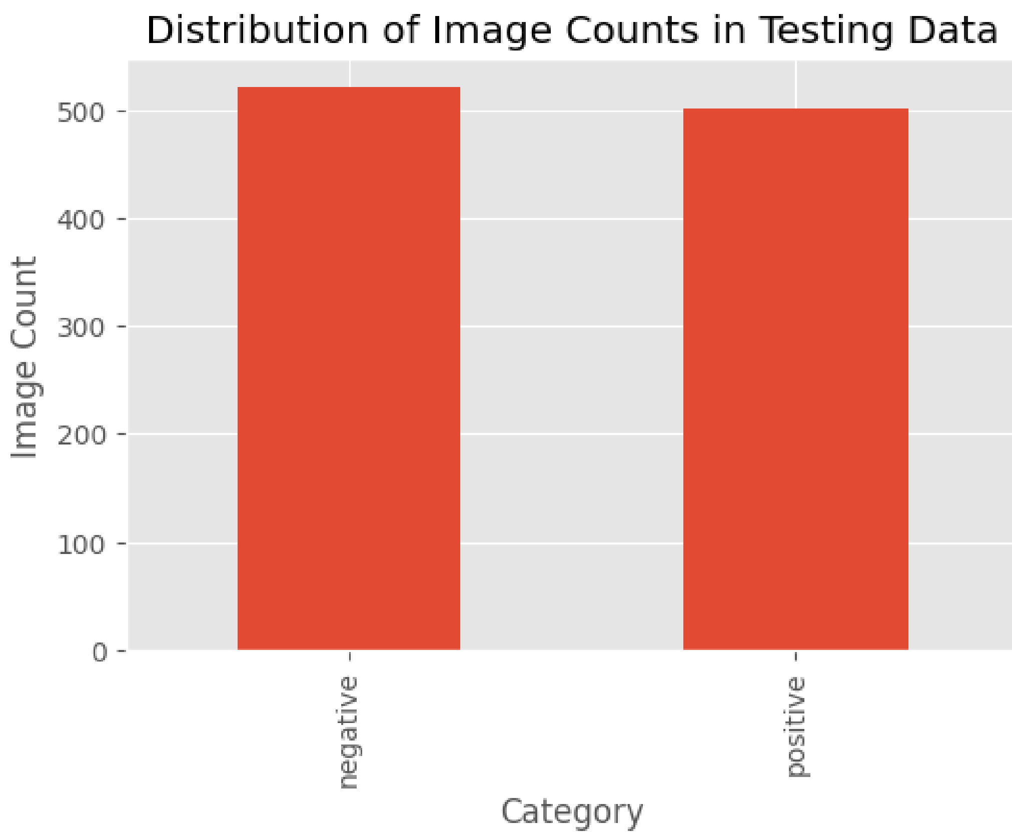
[12]:
```
plt.figure(figsize=(6,4))
trn_df['labels'].value_counts().plot(kind='bar')
plt.title('Distribution of Image Counts in Training Data')
plt.xlabel('Category')
plt.ylabel('Image Count')
plt.show()
```



Negative images slightly outnumber the positive ones, but are close enough to continue without additional data wrangling

4.2 | Look at Testing Images' Distribution

[13]:
```
plt.figure(figsize=(6,4))
tst_df['labels'].value_counts().plot(kind='bar')
plt.title('Distribution of Image Counts in Testing Data')
plt.xlabel('Category')
plt.ylabel('Image Count')
plt.show()
```



Distribution mirrors what the *training data* shows, but with less frequency.

4.3 | Examine Shape of Training and Testing DataFrames

[14]:
```
print('Training Shape: \n', trn_df.shape)
print('Testing Shape:  \n', tst_df.shape)
```

```
Training Shape:
 (4076, 2)
Testing Shape:
 (1024, 2)
```

NOTE: Since the dataframes are built from the contents of the image directories, there should be no missing values or duplicates.

4.0 | Data Wrangling

4.1 | Create a Validation Subset from Training Data I will use `flow_from_dataframe()` to create datasets for model training; therefore, no reason to create a new directory structure for validation data

[15]:
```
val_df, trn_df = train_test_split(trn_df, train_size=0.2, random_state=42,
                                  stratify=trn_df['labels'])
print(val_df.sample(10).to_markdown())
print(f'Validation Shape: {val_df.shape}')
```

```
|      | paths
| labels   |
|-----:|:--------------------------------------------------------------------------------
--------------------------|:---------|
| 2341 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(404).jpg       | positive |
| 1615 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(830).jpg       | positive |
| 3949 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (595).jpg   | negative |
| 2158 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(1965).jpg      | positive |
|   51 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(1479).jpg      | positive |
| 1967 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (1274).jpg | negative |
| 3644 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/positive/Cancer
(2414).jpg      | positive |
| 2917 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (546).jpg   | negative |
| 1429 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (225).jpg   | negative |
| 2855 |
/home/wiley/regis/dataScience/kaggleProject/images/data/training/negative/Not
Cancer  (1673).jpg | negative |
Validation Shape: (815, 2)
```

4.2 | Process Images from DataFrames Image augmentation will be used on the training and validation datasets. The test images will just be normalized.

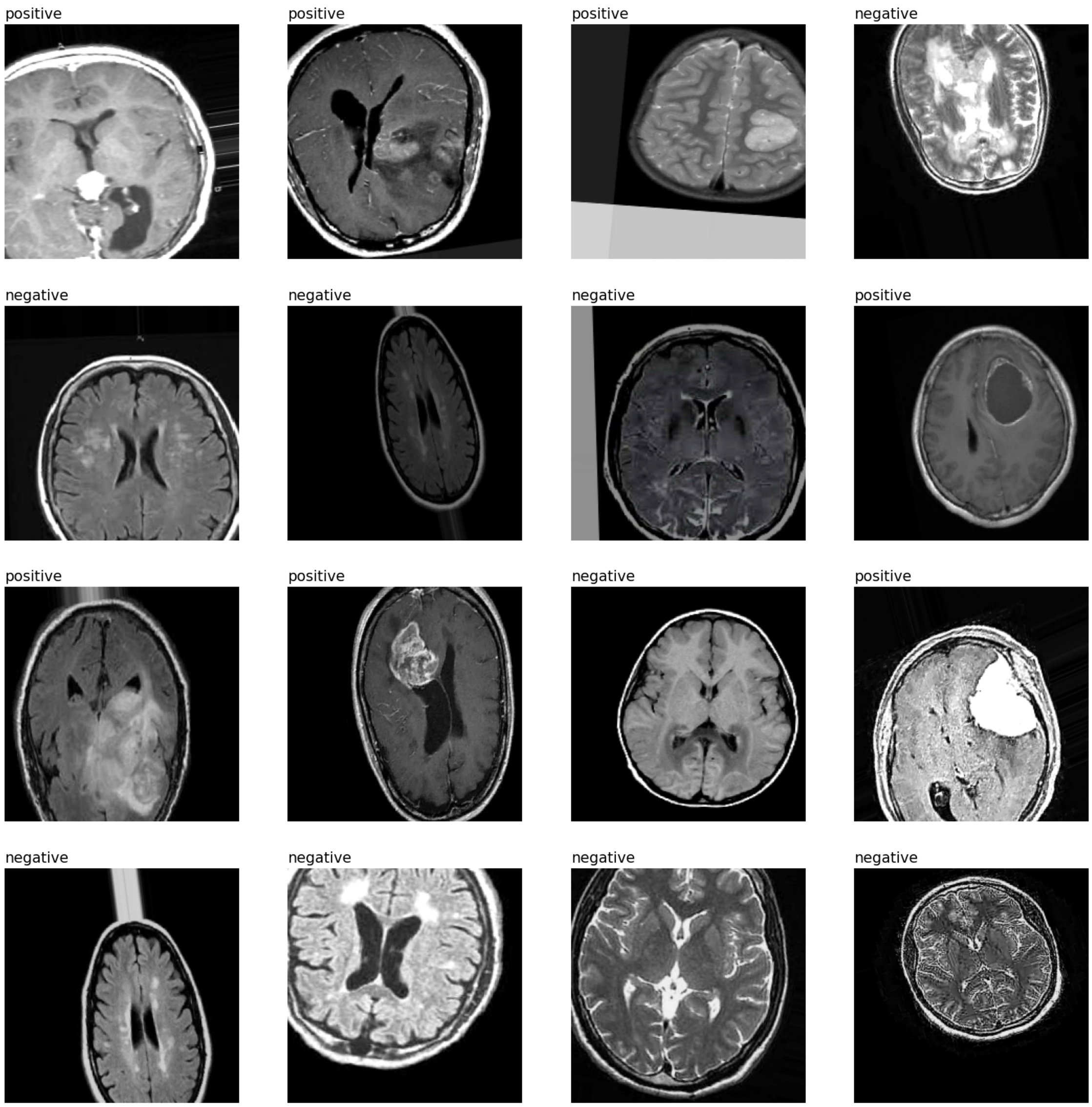
[16]:
```
# Apply image augmentation
gen = ImageDataGenerator(rescale=1./255,
                         brightness_range=(0.5, 1.5),
                         rotation_range=20,
```

```
                         width_shift_range=0.2,
                         height_shift_range=0.2,
                         shear_range=0.2,
                         zoom_range=0.2)

# The test dataset should not be augmented
# just rescaled
tst_gen = ImageDataGenerator(rescale=1./255)

# Create training datagen set
trn_gen = gen.flow_from_dataframe(trn_df, x_col='paths', y_col='labels',
                                  batch_size=batch_size, target_size=img_size,
                                  shuffle=True)

# Create validation datagen set
val_gen = gen.flow_from_dataframe(val_df, x_col='paths', y_col='labels',
                                  batch_size=batch_size, target_size=img_size,
                                  shuffle=True)

# Create test datagen set
tst_gen = tst_gen.flow_from_dataframe(tst_df, x_col='paths', y_col='labels',
                                      batch_size=16, target_size=img_size,
                                      shuffle=False)
```

```
Found 3261 validated image filenames belonging to 2 classes.
Found 815 validated image filenames belonging to 2 classes.
Found 1024 validated image filenames belonging to 2 classes.
```

4.3 | Examine a few Augmented Images and their Labels The images displayed have been augmented in the previous step. The appearance may not be consistent with non-augmented images.

[17]:
```
# Print augmented images from training dataset
print_images(trn_gen)
```



5.0 | Configure Training Values

5.1 | Basic Values

[18]:
```
# Number of training epochs
epochs = 50

# Steps per epoch
steps_per_ep = trn_gen.samples // batch_size

# Validation steps
val_steps = val_gen.samples // batch_size
```

```python
print(f'Image shape:      {img_shape}')
print(f'Epochs:           {epochs}')
print(f'Batch size:       {batch_size}')
print(f'Steps per epoch:  {steps_per_ep}')
print(f'Validation steps: {val_steps}')
```

```
Image shape:      (224, 224, 3)
Epochs:           50
Batch size:       64
Steps per epoch:  50
Validation steps: 12
```

5.2 | Define Callbacks With these *callbacks* the model's training will stop if the training loss stops decreasing (`EarlyStopping()`), and the learning rate will be reduced until the validation loss plateaus (`ReduceLROnPlateau()`)

[19]:
```python
# Define early_stop callback
early_stop = EarlyStopping(monitor='val_loss', min_delta=0.000000001,␣
 ↪patience=5,
                           baseline=None, restore_best_weights=True,␣
 ↪start_from_epoch=0)

# Define reduce LR on Plateau callback
reduceLRO = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=8,␣
 ↪mode='auto',
                              min_delta=0.0001, cooldown=0, min_lr=0)
```

6.0 | Baseline Model ### Define Model's Architecture

6.1 | Define Model's Architecture The CNN model is being defined by using `models.Sequential()` method. It consists of four convolution layers flattened into two fully connected layers with dropout. The output layer will use the *softmax* activation function instead of *relu*

[20]:
```python
backend.clear_session()

model_cnn = models.Sequential([
    # Conv layer #1
    Conv2D(32, (4,4), activation='relu', input_shape=img_shape),
    MaxPooling2D(pool_size=(3,3)),

    # Conv layer #2
    Conv2D(64, (4,4), activation='relu'),
    MaxPooling2D(pool_size=(3,3)),

    # Conv layer #3
```

```python
    Conv2D(128, (4,4), activation='relu'),
    MaxPooling2D(pool_size=(4,4)),

    # Conv layer #4
    Conv2D(128, (4,4), activation='relu'),
    Flatten(),

    # Fully connect layers
    Dense(512, activation='relu'),
    Dropout(0.5, seed=42),
    Dense(num_classes, activation='softmax')
])

model_cnn.summary()
```

```
I0000 00:00:1741353102.333307 1061755 gpu_device.cc:2022] Created device
/job:localhost/replica:0/task:0/device:GPU:0 with 9655 MB memory:  -> device: 0,
name: NVIDIA GeForce RTX 4070, pci bus id: 0000:09:00.0, compute capability: 8.9
```

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 221, 221, 32)	1,568
max_pooling2d (MaxPooling2D)	(None, 73, 73, 32)	0
conv2d_1 (Conv2D)	(None, 70, 70, 64)	32,832
max_pooling2d_1 (MaxPooling2D)	(None, 23, 23, 64)	0
conv2d_2 (Conv2D)	(None, 20, 20, 128)	131,200
max_pooling2d_2 (MaxPooling2D)	(None, 5, 5, 128)	0
conv2d_3 (Conv2D)	(None, 2, 2, 128)	262,272
flatten (Flatten)	(None, 512)	0
dense (Dense)	(None, 512)	262,656
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 2)	1,026

Total params: 691,554 (2.64 MB)

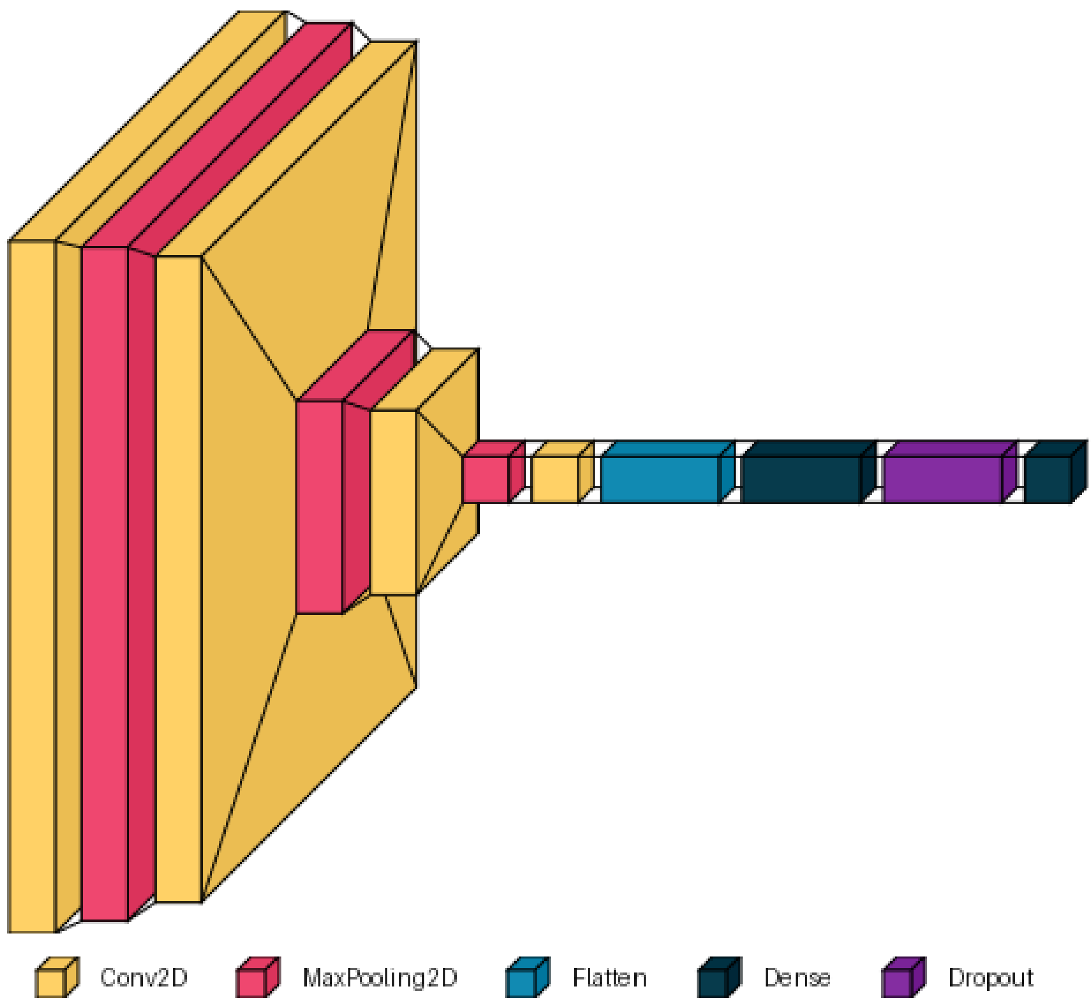
Trainable params: 691,554 (2.64 MB)

Non-trainable params: 0 (0.00 B)

6.2 | Visualize Layers

[21]:
```
layered_view(model_cnn, legend=True, max_xy=300)
```

[21]:



6.3 | Compile and Train Model The `Adam()` optimizer was selected for this model, since it is well suited to classification problems. The loss function `categorical_crossentropy()` was also selected for the same reason.

[22]:
```python
# Configure Adam optimizer
opt = optimizers.Adam(learning_rate=0.001, beta_1=0.869, beta_2=0.995)

# Compile base model
model_cnn.compile(optimizer=opt, loss='categorical_crossentropy',
                  metrics=['accuracy', tf.keras.metrics.
 ↪Precision(name='precision'),
                           tf.keras.metrics.Recall(name='recall'),
                           tf.keras.metrics.AUC(curve='PR', name='auc')])

# Fit data to model and record training history
hist_cnn = model_cnn.fit(trn_gen, batch_size=batch_size,␣
 ↪steps_per_epoch=steps_per_ep,
                         epochs=epochs, validation_data=val_gen,
                         validation_steps=val_steps,
                         callbacks=[early_stop, reduceLRO])
```

```
Epoch 1/50

WARNING: All log messages before absl::InitializeLog() is called are written to
STDERR
I0000 00:00:1741353106.745184 1061881 service.cc:148] XLA service 0x7f4df400e490
initialized for platform CUDA (this does not guarantee that XLA will be used).
Devices:
I0000 00:00:1741353106.745233 1061881 service.cc:156]   StreamExecutor device
(0): NVIDIA GeForce RTX 4070, Compute Capability 8.9
I0000 00:00:1741353107.080437 1061881 cuda_dnn.cc:529] Loaded cuDNN version
90300

 2/50              1s 30ms/step - accuracy:
0.5586 - auc: 0.5534 - loss: 0.6881 - precision: 0.5586 - recall: 0.5586

I0000 00:00:1741353112.356672 1061881 device_compiler.h:188] Compiled cluster
using XLA!  This line is logged at most once for the lifetime of the process.

50/50              51s 871ms/step -
accuracy: 0.5306 - auc: 0.5328 - loss: 0.6923 - precision: 0.5306 - recall:
0.5306 - val_accuracy: 0.6393 - val_auc: 0.6944 - val_loss: 0.6324 -
val_precision: 0.6393 - val_recall: 0.6393 - learning_rate: 0.0010
Epoch 2/50
50/50              2s 45ms/step -
accuracy: 0.5938 - auc: 0.6172 - loss: 0.6800 - precision: 0.5938 - recall:
0.5938 - val_accuracy: 0.6596 - val_auc: 0.6854 - val_loss: 0.6482 -
val_precision: 0.6596 - val_recall: 0.6596 - learning_rate: 0.0010
Epoch 3/50
50/50              36s 715ms/step -
accuracy: 0.6037 - auc: 0.6497 - loss: 0.6522 - precision: 0.6037 - recall:
0.6037 - val_accuracy: 0.6706 - val_auc: 0.7165 - val_loss: 0.6147 -
val_precision: 0.6706 - val_recall: 0.6706 - learning_rate: 0.0010
Epoch 4/50
```

```
50/50            0s 9ms/step -
accuracy: 0.6562 - auc: 0.7581 - loss: 0.5873 - precision: 0.6562 - recall:
0.6562 - val_accuracy: 0.6809 - val_auc: 0.7505 - val_loss: 0.5871 -
val_precision: 0.6809 - val_recall: 0.6809 - learning_rate: 0.0010
Epoch 5/50
50/50            37s 740ms/step -
accuracy: 0.6705 - auc: 0.7234 - loss: 0.6092 - precision: 0.6705 - recall:
0.6705 - val_accuracy: 0.6927 - val_auc: 0.7392 - val_loss: 0.5985 -
val_precision: 0.6927 - val_recall: 0.6927 - learning_rate: 0.0010
Epoch 6/50
50/50            0s 8ms/step -
accuracy: 0.6875 - auc: 0.7597 - loss: 0.5928 - precision: 0.6875 - recall:
0.6875 - val_accuracy: 0.6383 - val_auc: 0.7021 - val_loss: 0.6326 -
val_precision: 0.6383 - val_recall: 0.6383 - learning_rate: 0.0010
Epoch 7/50
50/50            36s 730ms/step -
accuracy: 0.7052 - auc: 0.7530 - loss: 0.5826 - precision: 0.7052 - recall:
0.7052 - val_accuracy: 0.7292 - val_auc: 0.8091 - val_loss: 0.5356 -
val_precision: 0.7292 - val_recall: 0.7292 - learning_rate: 0.0010
Epoch 8/50
50/50            0s 7ms/step -
accuracy: 0.7812 - auc: 0.8344 - loss: 0.5043 - precision: 0.7812 - recall:
0.7812 - val_accuracy: 0.7234 - val_auc: 0.7876 - val_loss: 0.5562 -
val_precision: 0.7234 - val_recall: 0.7234 - learning_rate: 0.0010
Epoch 9/50
50/50            37s 733ms/step -
accuracy: 0.7304 - auc: 0.8011 - loss: 0.5370 - precision: 0.7304 - recall:
0.7304 - val_accuracy: 0.7656 - val_auc: 0.8459 - val_loss: 0.4833 -
val_precision: 0.7656 - val_recall: 0.7656 - learning_rate: 0.0010
Epoch 10/50
50/50            0s 9ms/step -
accuracy: 0.7031 - auc: 0.8151 - loss: 0.5235 - precision: 0.7031 - recall:
0.7031 - val_accuracy: 0.7234 - val_auc: 0.8404 - val_loss: 0.4787 -
val_precision: 0.7234 - val_recall: 0.7234 - learning_rate: 0.0010
Epoch 11/50
50/50            37s 744ms/step -
accuracy: 0.7620 - auc: 0.8408 - loss: 0.4894 - precision: 0.7620 - recall:
0.7620 - val_accuracy: 0.8112 - val_auc: 0.8857 - val_loss: 0.4263 -
val_precision: 0.8112 - val_recall: 0.8112 - learning_rate: 0.0010
Epoch 12/50
50/50            0s 8ms/step -
accuracy: 0.8594 - auc: 0.9352 - loss: 0.3441 - precision: 0.8594 - recall:
0.8594 - val_accuracy: 0.7447 - val_auc: 0.8786 - val_loss: 0.4425 -
val_precision: 0.7447 - val_recall: 0.7447 - learning_rate: 0.0010
Epoch 13/50
50/50            37s 740ms/step -
accuracy: 0.7924 - auc: 0.8668 - loss: 0.4509 - precision: 0.7924 - recall:
0.7924 - val_accuracy: 0.8112 - val_auc: 0.8961 - val_loss: 0.4093 -
```

```
val_precision: 0.8112 - val_recall: 0.8112 - learning_rate: 0.0010
Epoch 14/50
50/50            0s 8ms/step -
accuracy: 0.9375 - auc: 0.9503 - loss: 0.3114 - precision: 0.9375 - recall:
0.9375 - val_accuracy: 0.7872 - val_auc: 0.8959 - val_loss: 0.4117 -
val_precision: 0.7872 - val_recall: 0.7872 - learning_rate: 0.0010
Epoch 15/50
50/50            37s 741ms/step -
accuracy: 0.8155 - auc: 0.8947 - loss: 0.4080 - precision: 0.8155 - recall:
0.8155 - val_accuracy: 0.8008 - val_auc: 0.8899 - val_loss: 0.4169 -
val_precision: 0.8008 - val_recall: 0.8008 - learning_rate: 0.0010
Epoch 16/50
50/50            0s 8ms/step -
accuracy: 0.8438 - auc: 0.9166 - loss: 0.3569 - precision: 0.8438 - recall:
0.8438 - val_accuracy: 0.8085 - val_auc: 0.8743 - val_loss: 0.4356 -
val_precision: 0.8085 - val_recall: 0.8085 - learning_rate: 0.0010
Epoch 17/50
50/50            36s 732ms/step -
accuracy: 0.8149 - auc: 0.9030 - loss: 0.3939 - precision: 0.8149 - recall:
0.8149 - val_accuracy: 0.8203 - val_auc: 0.9057 - val_loss: 0.3907 -
val_precision: 0.8203 - val_recall: 0.8203 - learning_rate: 0.0010
Epoch 18/50
50/50            0s 8ms/step -
accuracy: 0.8438 - auc: 0.9221 - loss: 0.3516 - precision: 0.8438 - recall:
0.8438 - val_accuracy: 0.7447 - val_auc: 0.8458 - val_loss: 0.5851 -
val_precision: 0.7447 - val_recall: 0.7447 - learning_rate: 0.0010
Epoch 19/50
50/50            37s 736ms/step -
accuracy: 0.8277 - auc: 0.8998 - loss: 0.4019 - precision: 0.8277 - recall:
0.8277 - val_accuracy: 0.8424 - val_auc: 0.9076 - val_loss: 0.3950 -
val_precision: 0.8424 - val_recall: 0.8424 - learning_rate: 0.0010
Epoch 20/50
50/50            0s 9ms/step -
accuracy: 0.8438 - auc: 0.8893 - loss: 0.4323 - precision: 0.8438 - recall:
0.8438 - val_accuracy: 0.8298 - val_auc: 0.9323 - val_loss: 0.3585 -
val_precision: 0.8298 - val_recall: 0.8298 - learning_rate: 0.0010
Epoch 21/50
50/50            36s 726ms/step -
accuracy: 0.8385 - auc: 0.9164 - loss: 0.3666 - precision: 0.8385 - recall:
0.8385 - val_accuracy: 0.8320 - val_auc: 0.9117 - val_loss: 0.3758 -
val_precision: 0.8320 - val_recall: 0.8320 - learning_rate: 0.0010
Epoch 22/50
50/50            0s 8ms/step -
accuracy: 0.8438 - auc: 0.9418 - loss: 0.3178 - precision: 0.8438 - recall:
0.8438 - val_accuracy: 0.8298 - val_auc: 0.9107 - val_loss: 0.3680 -
val_precision: 0.8298 - val_recall: 0.8298 - learning_rate: 0.0010
Epoch 23/50
50/50            36s 724ms/step -
```

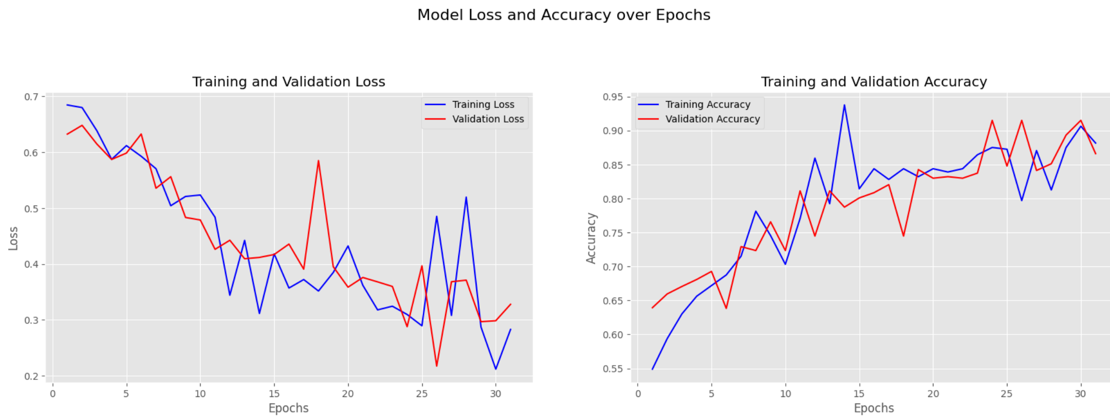
```
accuracy: 0.8650 - auc: 0.9297 - loss: 0.3365 - precision: 0.8650 - recall:
0.8650 - val_accuracy: 0.8372 - val_auc: 0.9212 - val_loss: 0.3598 -
val_precision: 0.8372 - val_recall: 0.8372 - learning_rate: 0.0010
Epoch 24/50
50/50            0s 8ms/step -
accuracy: 0.8750 - auc: 0.9436 - loss: 0.3096 - precision: 0.8750 - recall:
0.8750 - val_accuracy: 0.9149 - val_auc: 0.9532 - val_loss: 0.2877 -
val_precision: 0.9149 - val_recall: 0.9149 - learning_rate: 0.0010
Epoch 25/50
50/50            38s 758ms/step -
accuracy: 0.8708 - auc: 0.9478 - loss: 0.2942 - precision: 0.8708 - recall:
0.8708 - val_accuracy: 0.8477 - val_auc: 0.9152 - val_loss: 0.3967 -
val_precision: 0.8477 - val_recall: 0.8477 - learning_rate: 0.0010
Epoch 26/50
50/50            0s 8ms/step -
accuracy: 0.7969 - auc: 0.8602 - loss: 0.4852 - precision: 0.7969 - recall:
0.7969 - val_accuracy: 0.9149 - val_auc: 0.9760 - val_loss: 0.2173 -
val_precision: 0.9149 - val_recall: 0.9149 - learning_rate: 0.0010
Epoch 27/50
50/50            35s 694ms/step -
accuracy: 0.8734 - auc: 0.9456 - loss: 0.2979 - precision: 0.8734 - recall:
0.8734 - val_accuracy: 0.8411 - val_auc: 0.9185 - val_loss: 0.3682 -
val_precision: 0.8411 - val_recall: 0.8411 - learning_rate: 0.0010
Epoch 28/50
50/50            0s 8ms/step -
accuracy: 0.8125 - auc: 0.8774 - loss: 0.5196 - precision: 0.8125 - recall:
0.8125 - val_accuracy: 0.8511 - val_auc: 0.9133 - val_loss: 0.3710 -
val_precision: 0.8511 - val_recall: 0.8511 - learning_rate: 0.0010
Epoch 29/50
50/50            35s 694ms/step -
accuracy: 0.8758 - auc: 0.9538 - loss: 0.2780 - precision: 0.8758 - recall:
0.8758 - val_accuracy: 0.8932 - val_auc: 0.9438 - val_loss: 0.2967 -
val_precision: 0.8932 - val_recall: 0.8932 - learning_rate: 0.0010
Epoch 30/50
50/50            0s 8ms/step -
accuracy: 0.9062 - auc: 0.9808 - loss: 0.2117 - precision: 0.9062 - recall:
0.9062 - val_accuracy: 0.9149 - val_auc: 0.9371 - val_loss: 0.2984 -
val_precision: 0.9149 - val_recall: 0.9149 - learning_rate: 0.0010
Epoch 31/50
50/50            35s 694ms/step -
accuracy: 0.8754 - auc: 0.9506 - loss: 0.2864 - precision: 0.8754 - recall:
0.8754 - val_accuracy: 0.8659 - val_auc: 0.9352 - val_loss: 0.3278 -
val_precision: 0.8659 - val_recall: 0.8659 - learning_rate: 0.0010
```

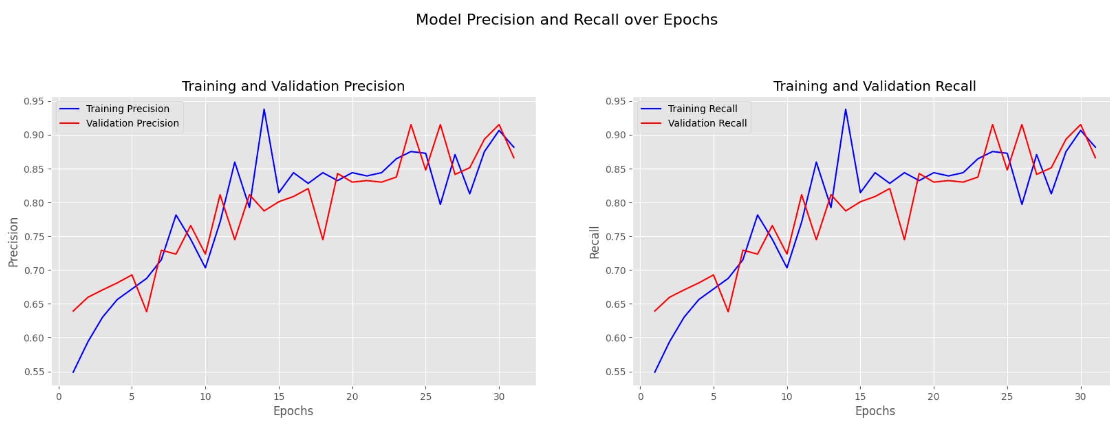
7.0 | Evaluate Performance

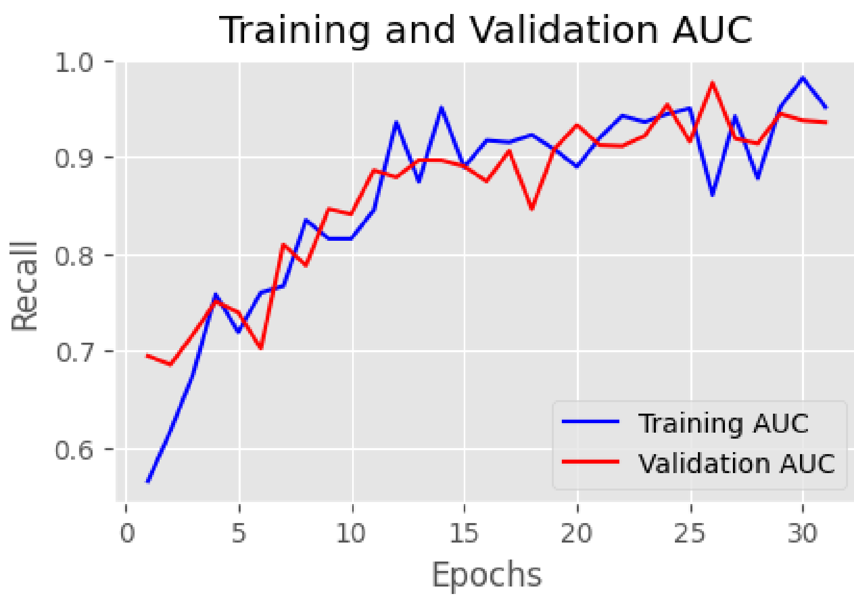
7.1 | Plot Training and Validation Metrics If the training and validation metrics diverge

significantly from each other, that can be an indication of overfitting.

[23]:
```
plot_history(hist_cnn)
```







7.2 | Score Model To evaluate the model's performance the following matrices will be evaluated against the test dataset: - **Model Loss** — gives a nuanced view of model optimization - **Model Accuracy** — provides the proportion of all classifications that were correct - **Precision** — shows how often a model is correct when predicting the target class - **Recall** — displays whether a model can find all objects of the target class - **Area Under Curve (AUC)** — compares the *true positive rate (TPR)* against the *false positive rate (FPR)* and shows how well the model distinguishes between the two classes - **F1 Score** — describes the harmonic mean of the precision and recall of the model

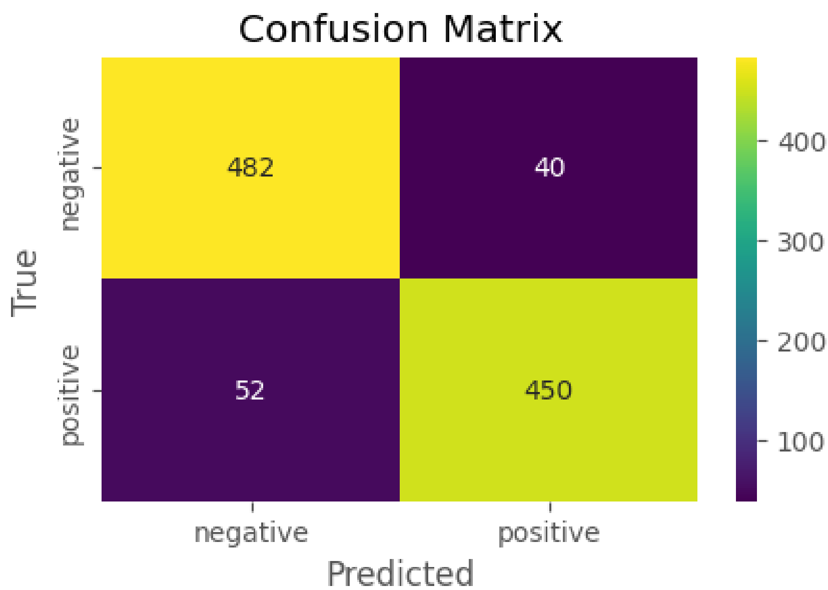
[24]:
```
score_model(model_cnn, tst_gen)
```

```
64/64              3s 22ms/step -
accuracy: 0.8981 - auc: 0.9610 - loss: 0.2521 - precision: 0.8981 - recall:
0.8981
------------------------------
Loss:      0.2208
Accuracy:  0.9102
Precision: 0.9102
Recall:    0.9696
AUC:       0.9102
F1 Score:  0.9389
------------------------------
```

7.3 | Plot Confusion Matrix A confusion matrix provides a visual representation of a model's performance when it comes to comparing true positives, false negatives, true negatives, and false positives.

[25]:
```
plot_cm(model_cnn, tst_gen)
```

```
64/64               2s 23ms/step
```



7.4 | Compute TPR and TNR The True Positive Rate (TPR) and True Negative Rate (TNR) are good indicators of how well the model is predicting positives (1s) and negatives (0s).

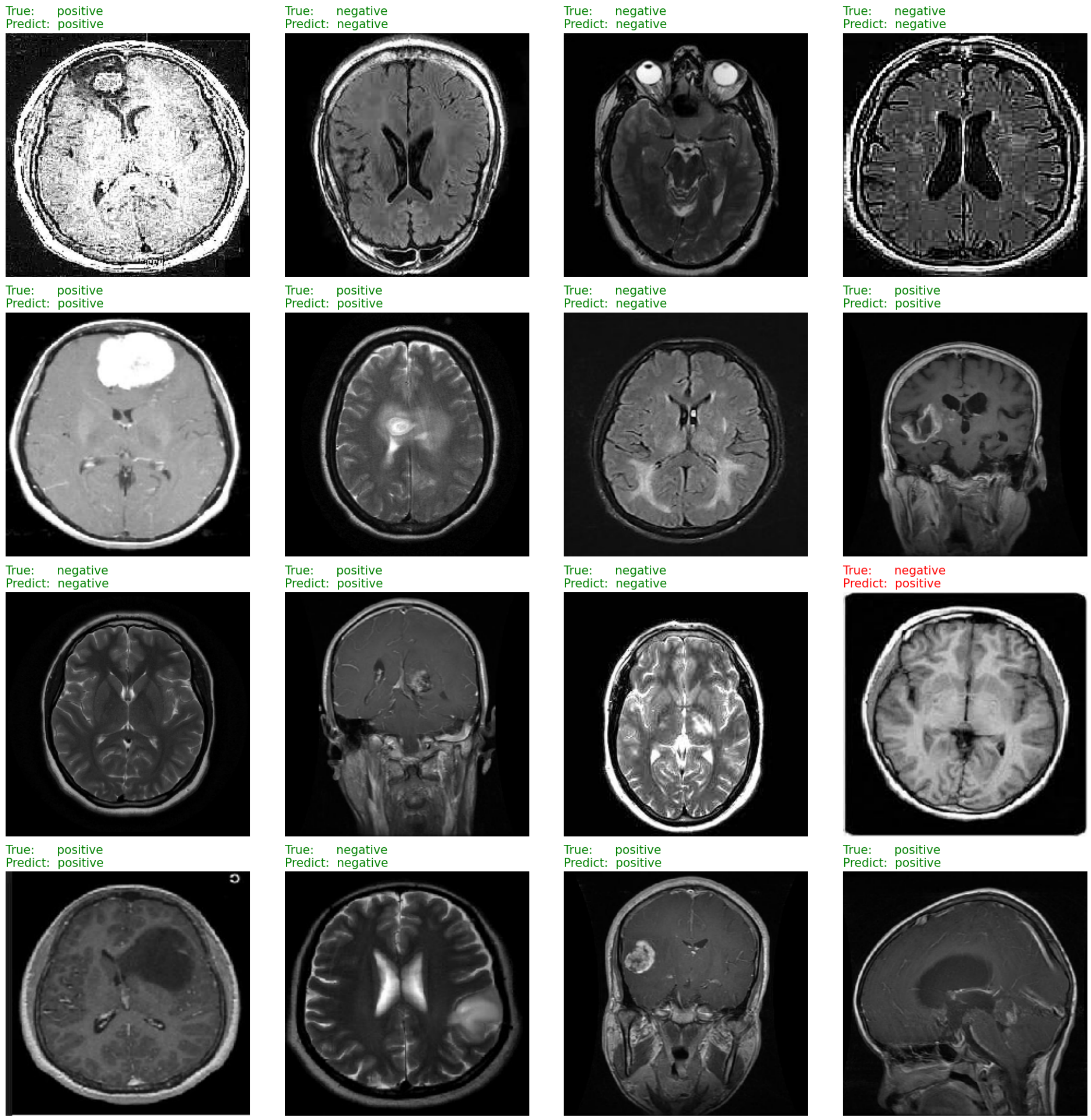
[26]:
```
compute_tpr(model_cnn, tst_gen)
```

```
64/64               1s 20ms/step
------------------------------
True Positive Rate (TPR): 0.8964
True Negative Rate (TNR): 0.9234
------------------------------
```

7.5 | View and Compare Predicted with True Labels If the ***True*** and ***Predict*** labels match, then the model accurately predicted the label of the image. This plot gives a visual representation of how well the model makes predictions between the two classes.

[27]:
```
display_preds(model_cnn, tst_gen)
```

```
1/1             0s 421ms/step
```



8.0 | Save Weights Weights can be used later for inference.

---

[28]:
```python
# Use date and time to create a unique filename
if save:
    now = datetime.now()
    date = now.strftime('%Y%m%d')
    time = now.strftime('%H%M%S')
    filename = date+time+'_cnn_brain_tumor.keras'

    # Save weights in keras zip format
    model_cnn.save('../weights/'+filename)
```

9.0 | Discussion and Conclusions

9.1 | General Performance The model is generalizing the test data well. The plots indicated the model is training well and overfitting is minimal. Training and Validation metrics closely follow each other during the training process and I do not see any items that are concerning. F1, True Positive, and True Negative scores are above 0.90 which indicates it is accurately predicting positive and negative labels with 90% accuracy.

9.2 | Further Work While the model is generalizing the test data with acceptable results, it can do better. I will conduct further research on CNN model tuning and keep experimenting until results are consistently in the high 90s.

[ ]:
```

```