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In [5]: #CNN +WAVELET+INT FUNTION
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In [12]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import (accuracy_score, roc_curve, auc, f1_score,
                             recall_score, precision_score, confusion_matrix,
                             classification_report, precision_recall_curve,
                             average_precision_score)

import os
import cv2
import tensorflow as tf
from tensorflow.keras import layers, models
import seaborn as sns
import pywt

# Define tumor classes
path = os.listdir('brain_tumor/Training/')
classes = {'no_tumor': 0, 'pituitary_tumor': 1}

# Load and preprocess data
X = []
Y = []
for cls in classes:
    pth = 'brain_tumor/Training/' + cls
    for j in os.listdir(pth):
        img = cv2.imread(pth + '/' + j, 0)
        img = cv2.resize(img, (200, 200))
        img_filtered = cv2.GaussianBlur(img, (5, 5), 0)
        X.append(img_filtered)
        Y.append(classes[cls])

X = np.array(X)
Y = np.array(Y)

# INT (Intensity Normalization Transformation) function
def int_function(image):
    # Normalize intensity values to [0, 1]
    normalized = (image - np.min(image)) / (np.max(image) - np.min(image) +
    # Scale to [0, 255] and convert to uint8
    return np.uint8(normalized * 255)

# Function to apply wavelet transform and INT function
def apply_wavelet_transform(image, wavelet='db1', level=1):
    # Apply wavelet transform
    coeffs = pywt.wavedec2(image, wavelet=wavelet, level=level)
    reconstructed_image = pywt.waverec2(coeffs, wavelet=wavelet)

    # Apply INT function
    reconstructed_image = int_function(reconstructed_image)

    # Resize to standard dimensions
    reconstructed_image = cv2.resize(reconstructed_image, (200, 200))
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    return reconstructed_image

# Apply wavelet transform with INT to each image
X_wavelet = np.array([apply_wavelet_transform(img) for img in X])

# Reshape and normalize data for CNN
X_wavelet_cnn = X_wavelet.reshape(len(X_wavelet), 200, 200, 1)
X_wavelet_cnn = X_wavelet_cnn / 255.0
Y_cnn = tf.keras.utils.to_categorical(Y, num_classes=2)

# Split the dataset
xtrain_wavelet_cnn, xtest_wavelet_cnn, ytrain_cnn, ytest_cnn = train_test_split(
    X_wavelet_cnn, Y_cnn, random_state=10, test_size=.20)

# Build Enhanced CNN model
def build_cnn_model(input_shape):
    model = models.Sequential([
        layers.Conv2D(32, (3, 3), activation='relu', input_shape=input_shape),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(64, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(128, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Conv2D(256, (3, 3), activation='relu'),
        layers.MaxPooling2D((2, 2)),
        layers.Flatten(),
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(128, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(2, activation='softmax')
    ])
    return model

# Initialize, compile and train CNN model
input_shape = (200, 200, 1)
cnn_model_wavelet = build_cnn_model(input_shape)
cnn_model_wavelet.compile(optimizer='adam',
                          loss='categorical_crossentropy',
                          metrics=['accuracy'])

history_cnn_wavelet = cnn_model_wavelet.fit(xtrain_wavelet_cnn, ytrain_cnn,
                                             epochs=10, batch_size=32,
                                             validation_data=(xtest_wavelet_cnn, ytest_cnn))

# Evaluate model
cnn_test_loss_wavelet, cnn_test_acc_wavelet = cnn_model_wavelet.evaluate(xtest_wavelet_cnn, ytest_cnn)
print(f"Enhanced CNN with Wavelet and INT Function Test Accuracy: {cnn_test_acc_wavelet}")

# Plot training history
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(history_cnn_wavelet.history['accuracy'], label='Training Accuracy')
plt.plot(history_cnn_wavelet.history['val_accuracy'], label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')

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plt.ylabel('Accuracy')
plt.legend()

plt.subplot(1, 2, 2)
plt.plot(history_cnn_wavelet.history['loss'], label='Training Loss')
plt.plot(history_cnn_wavelet.history['val_loss'], label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.tight_layout()
plt.show()

# Get predictions and metrics
cnn_probs_wavelet = cnn_model_wavelet.predict(xtest_wavelet_cnn[:, 1])
cnn_preds_classes_wavelet = np.argmax(cnn_model_wavelet.predict(xtest_wavelet_cnn[:, 1]), axis=1)
true_labels = np.argmax(ytest_cnn, axis=1)

# ROC Curve
fpr, tpr, _ = roc_curve(true_labels, cnn_probs_wavelet)
roc_auc = auc(fpr, tpr)

# Precision-Recall Curve
precision, recall, _ = precision_recall_curve(true_labels, cnn_probs_wavelet)
avg_precision = average_precision_score(true_labels, cnn_probs_wavelet)

# Plot ROC and Precision-Recall curves
plt.figure(figsize=(12, 5))

# ROC Curve
plt.subplot(1, 2, 1)
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic')
plt.legend(loc="lower right")

# Precision-Recall Curve
plt.subplot(1, 2, 2)
plt.plot(recall, precision, color='blue', lw=2, label=f'Precision-Recall curve (AP = {avg_precision:.2f})')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.ylim([0.0, 1.05])
plt.xlim([0.0, 1.0])
plt.title('Precision-Recall Curve')
plt.legend(loc="lower left")

plt.tight_layout()
plt.show()

# Confusion Matrix and Classification Report
conf_matrix = confusion_matrix(true_labels, cnn_preds_classes_wavelet)

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class_report = classification_report(true_labels, cnn_preds_classes_wavelet,
                                     target_names=['No Tumor', 'Pituitary Tum

print("Classification Report:")
print(class_report)

# Plot Confusion Matrix with counts and percentages
plt.figure(figsize=(6, 6))
group_counts = [{"0:0.0f}".format(value) for value in conf_matrix.flatten()]
group_percentages = [{"0:.1%}".format(value) for value in conf_matrix.flatte
labels = [f"{v1}\n({v2})" for v1, v2 in zip(group_counts, group_percentages)]
labels = np.asarray(labels).reshape(2, 2)

sns.heatmap(conf_matrix, annot=labels, fmt='', cmap='Blues', cbar=False,
            xticklabels=['No Tumor', 'Pituitary Tumor'],
            yticklabels=['No Tumor', 'Pituitary Tumor'],
            annot_kws={"fontsize":12})

plt.xlabel('Predicted Label', fontsize=12)
plt.ylabel('True Label', fontsize=12)
plt.title('Confusion Matrix\n(Counts with Percentages)', fontsize=13, pad=20)
plt.xticks(rotation=0)
plt.yticks(rotation=0)
plt.tight_layout()
plt.show()

# Calculate and print additional metrics
f1 = f1_score(true_labels, cnn_preds_classes_wavelet)
recall = recall_score(true_labels, cnn_preds_classes_wavelet)
precision = precision_score(true_labels, cnn_preds_classes_wavelet)

print(f"\nAdditional Metrics:")
print(f"F1 Score: {f1:.4f}")
print(f"Recall: {recall:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Average Precision: {avg_precision:.4f}")
print(f"ROC AUC: {roc_auc:.4f}")

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C:\Users\Ananda kumar sahu\AppData\Local\Programs\Python\Python312\Lib\site-packages\keras\src\layers\convolutional\base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```

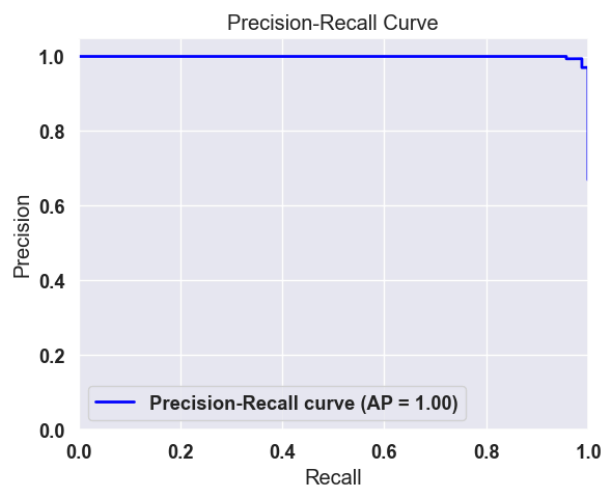
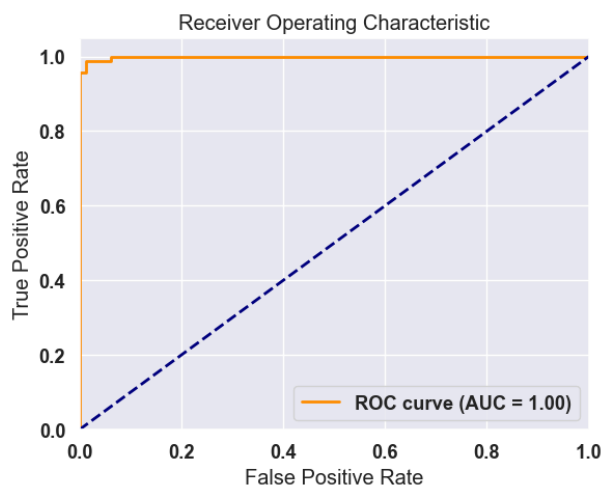
super().__init__(activity_regularizer=activity_regularizer, **kwargs)

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Epoch 1/10
31/31 ————— **24s** 718ms/step - accuracy: 0.6559 - loss: 0.6682
 - val_accuracy: 0.7143 - val_loss: 0.5216
 Epoch 2/10
31/31 ————— **22s** 702ms/step - accuracy: 0.7997 - loss: 0.4789
 - val_accuracy: 0.8980 - val_loss: 0.2888
 Epoch 3/10
31/31 ————— **22s** 704ms/step - accuracy: 0.9206 - loss: 0.2395
 - val_accuracy: 0.9551 - val_loss: 0.1340
 Epoch 4/10
31/31 ————— **22s** 720ms/step - accuracy: 0.9509 - loss: 0.1342
 - val_accuracy: 0.9633 - val_loss: 0.0917
 Epoch 5/10
31/31 ————— **22s** 708ms/step - accuracy: 0.9800 - loss: 0.0772
 - val_accuracy: 0.9796 - val_loss: 0.0480
 Epoch 6/10
31/31 ————— **22s** 702ms/step - accuracy: 0.9846 - loss: 0.0557
 - val_accuracy: 0.9837 - val_loss: 0.0469
 Epoch 7/10
31/31 ————— **22s** 712ms/step - accuracy: 0.9938 - loss: 0.0301
 - val_accuracy: 0.9796 - val_loss: 0.0558
 Epoch 8/10
31/31 ————— **22s** 710ms/step - accuracy: 0.9794 - loss: 0.0737
 - val_accuracy: 0.9878 - val_loss: 0.0316
 Epoch 9/10
31/31 ————— **22s** 720ms/step - accuracy: 0.9879 - loss: 0.0468
 - val_accuracy: 0.9878 - val_loss: 0.0448
 Epoch 10/10
31/31 ————— **23s** 726ms/step - accuracy: 0.9937 - loss: 0.0184
 - val_accuracy: 0.9837 - val_loss: 0.0652
8/8 ————— **1s** 164ms/step - accuracy: 0.9894 - loss: 0.0433
 Enhanced CNN with Wavelet and INT Function Test Accuracy: 0.9837



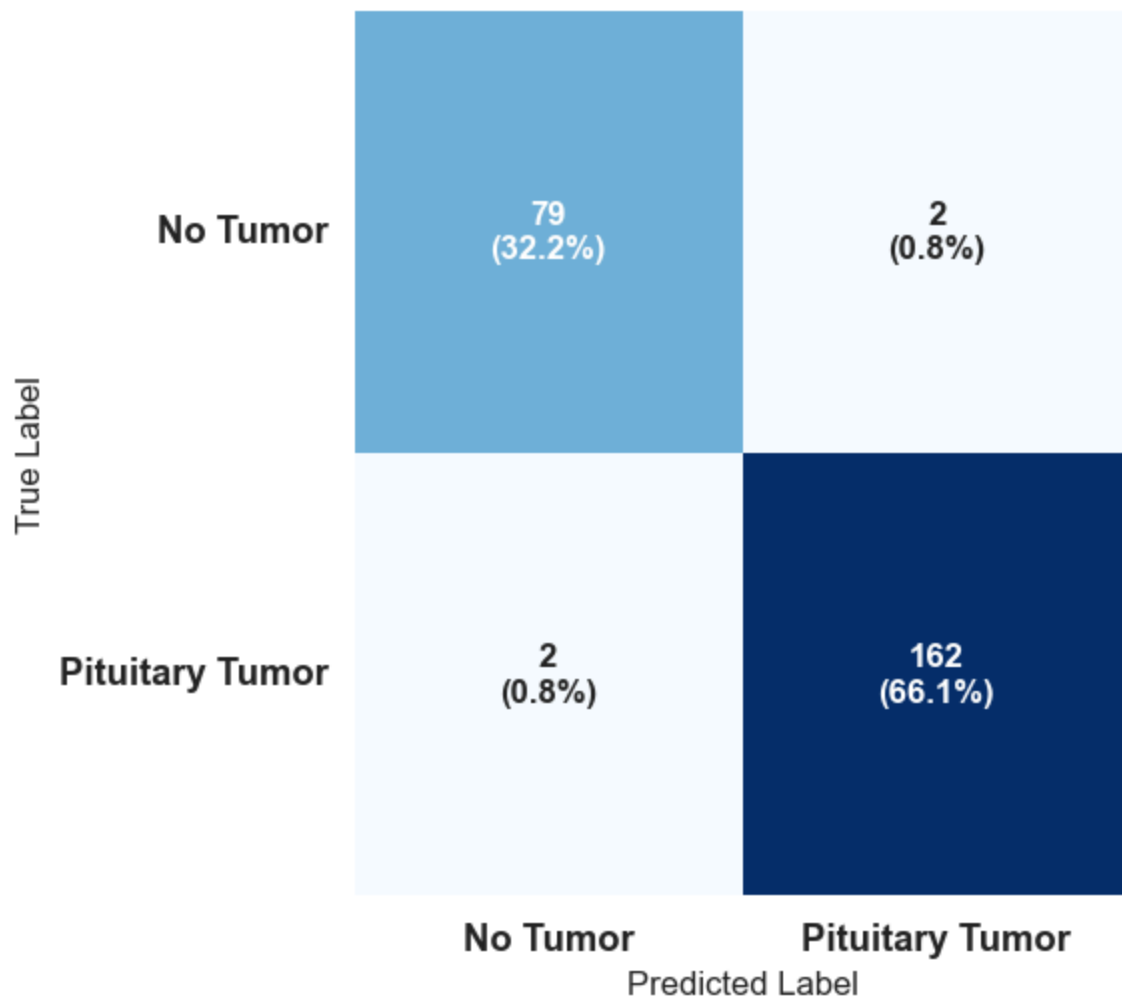
8/8 ————— **1s** 167ms/step
8/8 ————— **1s** 148ms/step



Classification Report:

	precision	recall	f1-score	support
No Tumor	0.98	0.98	0.98	81
Pituitary Tumor	0.99	0.99	0.99	164
accuracy			0.98	245
macro avg	0.98	0.98	0.98	245
weighted avg	0.98	0.98	0.98	245

Confusion Matrix
(Counts with Percentages)



Additional Metrics:
F1 Score: 0.9878
Recall: 0.9878
Precision: 0.9878
Average Precision: 0.9994
ROC AUC: 0.9989

In []: