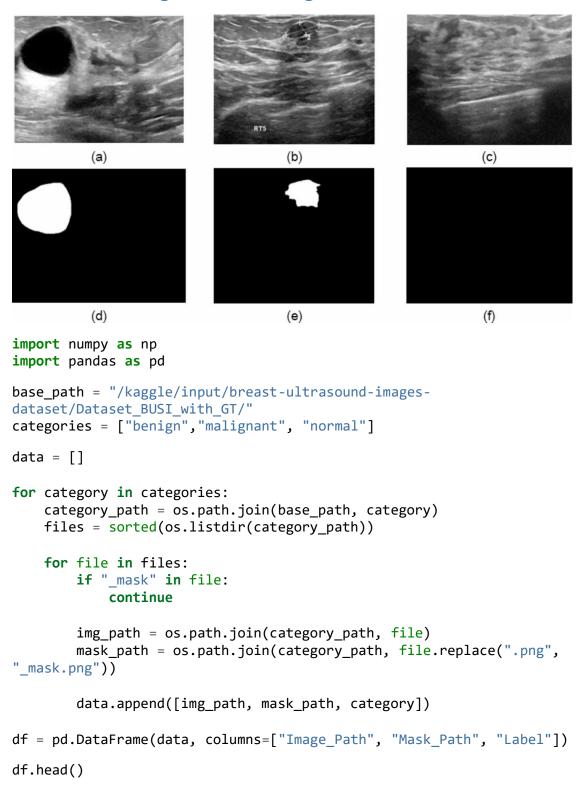
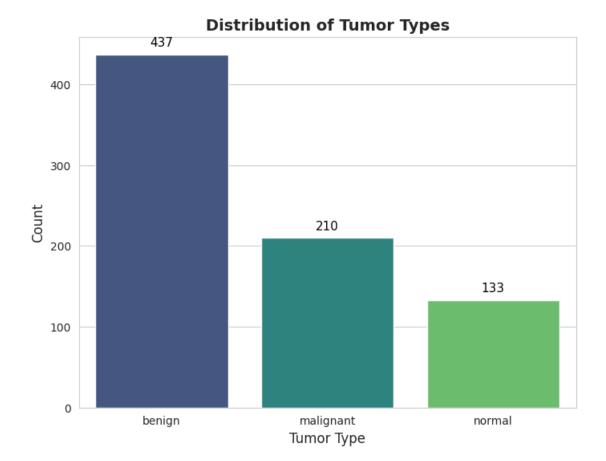
Breast Cancer Segmentation using HCMA - Unet Novel Architecture

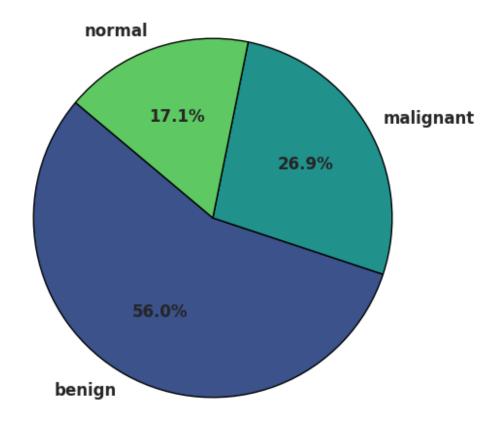


```
Image Path
  /kaggle/input/breast-ultrasound-images-dataset...
  /kaggle/input/breast-ultrasound-images-dataset...
1
2 /kaggle/input/breast-ultrasound-images-dataset...
3 /kaggle/input/breast-ultrasound-images-dataset...
4 /kaggle/input/breast-ultrasound-images-dataset...
                                           Mask_Path
                                                       Label
  /kaggle/input/breast-ultrasound-images-dataset...
                                                      benign
  /kaggle/input/breast-ultrasound-images-dataset...
                                                      benign
2 /kaggle/input/breast-ultrasound-images-dataset...
                                                      benign
  /kaggle/input/breast-ultrasound-images-dataset...
                                                      benign
4 /kaggle/input/breast-ultrasound-images-dataset...
                                                      benign
df.tail()
                                            Image_Path
775
    /kaggle/input/breast-ultrasound-images-dataset...
776
    /kaggle/input/breast-ultrasound-images-dataset...
777
    /kaggle/input/breast-ultrasound-images-dataset...
    /kaggle/input/breast-ultrasound-images-dataset...
778
779
     /kaggle/input/breast-ultrasound-images-dataset...
                                                         Label
                                             Mask Path
     /kaggle/input/breast-ultrasound-images-dataset...
                                                        normal
775
776
    /kaggle/input/breast-ultrasound-images-dataset...
                                                        normal
    /kaggle/input/breast-ultrasound-images-dataset...
777
                                                        normal
     /kaggle/input/breast-ultrasound-images-dataset...
778
                                                        normal
779
    /kaggle/input/breast-ultrasound-images-dataset...
                                                        normal
df.shape
(780, 3)
df.columns
Index(['Image_Path', 'Mask_Path', 'Label'], dtype='object')
df.duplicated().sum()
0
df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 780 entries, 0 to 779
Data columns (total 3 columns):
                 Non-Null Count Dtype
#
    Column
                 _____
     Image Path 780 non-null
                                 object
 1
    Mask Path
                 780 non-null
                                 object
 2
     Label
                 780 non-null
                                 object
```

```
dtvpes: object(3)
memory usage: 18.4+ KB
df['Label'].unique()
array(['benign', 'malignant', 'normal'], dtype=object)
df['Label'].value_counts()
Label
benign
             437
malignant
             210
normal
             133
Name: count, dtype: int64
import seaborn as sns
import matplotlib.pyplot as plt
sns.set_style("whitegrid")
fig, ax = plt.subplots(figsize=(8, 6))
sns.countplot(data=df, x="Label", palette="viridis", ax=ax)
ax.set_title("Distribution of Tumor Types", fontsize=14, fontweight='bold')
ax.set xlabel("Tumor Type", fontsize=12)
ax.set_ylabel("Count", fontsize=12)
for p in ax.patches:
    ax.annotate(f'{int(p.get height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='bottom', fontsize=11, color='black',
                xytext=(0, 5), textcoords='offset points')
plt.show()
label_counts = df["Label"].value_counts()
fig, ax = plt.subplots(figsize=(8, 6))
colors = sns.color palette("viridis", len(label counts))
ax.pie(label_counts, labels=label_counts.index, autopct='%1.1f%%',
       startangle=140, colors=colors, textprops={'fontsize': 12, 'weight':
'bold'},
       wedgeprops={'edgecolor': 'black', 'linewidth': 1})
ax.set_title("Distribution of Tumor Types - Pie Chart", fontsize=14,
fontweight='bold')
plt.show()
```



Distribution of Tumor Types - Pie Chart



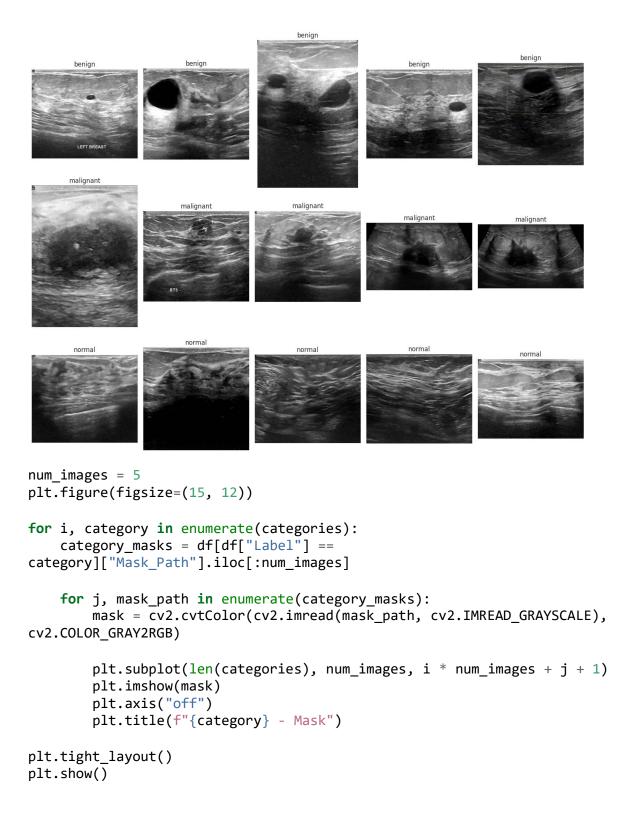
```
import cv2

num_images = 5
plt.figure(figsize=(15, 12))

for i, category in enumerate(categories):
    category_images = df[df["Label"] ==
category]["Image_Path"].iloc[:num_images]

    for j, img_path in enumerate(category_images):
        img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
        plt.subplot(len(categories), num_images, i * num_images + j + 1)
        plt.imshow(img)
        plt.axis("off")
        plt.title(category)

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



```
benign - Mask
                    benign - Mask
    benign - Mask
                                                    benign - Mask
    malignant - Mask
                                   malignant - Mask
                    malignant - Mask
                    normal - Mask
                                                    normal - Mask
    normal - Mask
                                    normal - Mask
                                                                    normal - Mask
num_images = 5
plt.figure(figsize=(15, 12))
for i, category in enumerate(categories):
    category_images = df[df["Label"] ==
category]["Image_Path"].iloc[:num_images]
    category_masks = df[df["Label"] ==
category]["Mask_Path"].iloc[:num_images]
    for j, (img_path, mask_path) in enumerate(zip(category_images,
category_masks)):
         img = cv2.cvtColor(cv2.imread(img_path), cv2.COLOR_BGR2RGB)
         mask = cv2.cvtColor(cv2.imread(mask_path, cv2.IMREAD_GRAYSCALE),
cv2.COLOR_GRAY2RGB)
         plt.subplot(len(categories), num_images * 2, i * num_images * 2 + j *
2 + 1)
         plt.imshow(img)
         plt.axis("off")
         plt.title(f"{category} - Image")
         plt.subplot(len(categories), num_images * 2, i * num_images * 2 + j *
2 + 2)
         plt.imshow(mask)
```

```
plt.axis("off")
         plt.title(f"{category} - Mask")
plt.tight_layout()
plt.show()
                                       benign - Mask
 benign - Image
         benign - Mask
                benign - Image
                                               benign - Image
                                                      benign - Mask
malignant - Imagemalignant - Mask
 normal - Image
from sklearn.preprocessing import LabelEncoder
label_encoder = LabelEncoder()
df['category_encoded'] = label_encoder.fit_transform(df['Label'])
from imblearn.over_sampling import RandomOverSampler
X = df[['Image_Path', 'Mask_Path']]
y = df['category_encoded']
ros = RandomOverSampler(random_state=42)
X_resampled, y_resampled = ros.fit_resample(X, y)
df_resampled = pd.DataFrame(X_resampled, columns=['Image_Path', 'Mask_Path'])
df_resampled['category_encoded'] = y_resampled
df_resampled.columns
Index(['Image_Path', 'Mask_Path', 'category_encoded'], dtype='object')
df_resampled['category_encoded'].value_counts()
```

```
category_encoded
0
     437
1
     437
2
    437
Name: count, dtype: int64
df resampled['category encoded'] =
df resampled['category encoded'].astype(str)
from sklearn.model selection import train test split
from sklearn.metrics import confusion matrix, classification report
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense,
Activation, Dropout, BatchNormalization
from tensorflow.keras import regularizers
import warnings
warnings.filterwarnings("ignore")
print ('check')
check
train df new, temp df new = train test split(
    df_resampled,
    train size=0.8,
    shuffle=True,
    random state=42,
    stratify=df resampled['category encoded']
)
valid df new, test df new = train test split(
    temp_df_new,
    test_size=0.5,
    shuffle=True,
    random state=42,
    stratify=temp df new['category encoded']
)
import tensorflow as tf
import numpy as np
import os
import cv2
from tensorflow.keras.layers import Conv3D, Conv3DTranspose,
BatchNormalization, Activation, Add, Input
from tensorflow.keras.models import Model
```

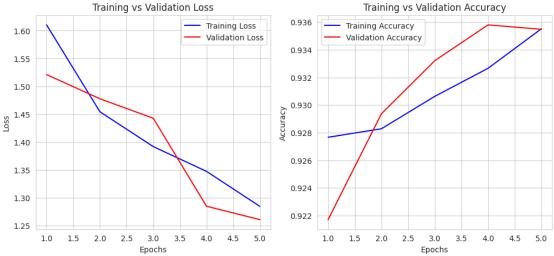
```
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.losses import BinaryCrossentropy
from sklearn.model selection import train test split
def load_images_and_masks(image_paths, mask_paths):
    images, masks = [], []
    for img_path, mask_path in zip(image_paths, mask_paths):
        image = cv2.imread(img path, cv2.IMREAD GRAYSCALE)
        image = cv2.resize(image, (128, 128)) / 255.0
        mask = cv2.imread(mask_path, cv2.IMREAD_GRAYSCALE)
        mask = cv2.resize(mask, (128, 128)) / 255.0
        images.append(image)
        masks.append(mask)
    return np.array(images)[..., np.newaxis], np.array(masks)[...,
np.newaxis]
X train, Y train = load images and masks(train df new['Image Path'].values,
train_df_new['Mask_Path'].values)
X_val, Y_val = load_images_and_masks(valid_df_new['Image_Path'].values,
valid_df_new['Mask_Path'].values)
X_test, Y_test = load_images_and_masks(test_df_new['Image_Path'].values,
test_df_new['Mask_Path'].values)
print(f"Training data shape: {X train.shape}, Training mask shape:
{Y train.shape}")
print(f"Validation data shape: {X val.shape}, Validation mask shape:
{Y_val.shape}")
print(f"Testing data shape: {X_test.shape}, Testing mask shape:
{Y test.shape}")
Training data shape: (1048, 128, 128, 1), Training mask shape: (1048, 128,
Validation data shape: (131, 128, 128, 1), Validation mask shape: (131, 128,
128, 1)
Testing data shape: (132, 128, 128, 1), Testing mask shape: (132, 128, 128,
1)
import tensorflow as tf
from tensorflow.keras.layers import Conv2D, Conv2DTranspose,
LayerNormalization, DepthwiseConv2D, concatenate, ReLU, Softmax
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import AdamW
import numpy as np
class ResBlock(tf.keras.layers.Layer):
    def __init__(self, filters, kernel_size=3, strides=1, padding='same'):
        super(ResBlock, self). init ()
        self.conv1 = Conv2D(filters, kernel_size, strides=strides,
padding=padding)
        self.conv2 = Conv2D(filters, kernel size, strides=strides,
```

```
padding=padding)
        self.relu = ReLU()
        self.match_dimensions = Conv2D(filters, kernel_size=1,
padding='same')
    def call(self, inputs):
        residual = inputs
        x = self.conv1(inputs)
       x = self.relu(x)
        x = self.conv2(x)
        residual = self.match_dimensions(residual)
        x += residual
        return self.relu(x)
class VSSB(tf.keras.layers.Layer):
    def __init__(self, filters):
        super(VSSB, self). init ()
        self.dwconv = DepthwiseConv2D(kernel size=11, strides=1,
padding='same')
        self.ln = LayerNormalization()
        self.linear = Conv2D(filters, kernel_size=1, strides=1,
padding='same')
    def call(self, inputs):
        x = self.dwconv(inputs)
        x = self.ln(x)
        x = self.linear(x)
        return x
class ISSA(tf.keras.layers.Layer):
    def __init__(self, filters):
        super(ISSA, self).__init__()
        self.ln = LayerNormalization()
        self.linear = Conv2D(filters, kernel size=1, strides=1,
padding='same')
    def call(self, inputs):
        x = self.ln(inputs)
        x = self.linear(x)
        return x
class MISM(tf.keras.layers.Layer):
    def __init__(self, filters):
        super(MISM, self).__init__()
        self.vssb = VSSB(filters)
        self.issa = ISSA(filters)
    def call(self, inputs):
        x = self.vssb(inputs)
```

```
x = self.issa(x)
        return x
class DenseBlock(tf.keras.layers.Layer):
    def __init__(self, filters):
        super(DenseBlock, self). init ()
        self.conv1 = Conv2D(filters, kernel_size=3, strides=1,
padding='same')
        self.conv2 = Conv2D(filters, kernel size=1, strides=1,
padding='same')
        self.conv3 = Conv2D(filters, kernel size=1, strides=1,
padding='same')
    def call(self, inputs):
        x1 = self.conv1(inputs)
        x2 = self.conv2(concatenate([inputs, x1]))
        x3 = self.conv3(concatenate([inputs, x1, x2]))
        return x3
class HCMA UNet(Model):
    def init (self):
        super(HCMA_UNet, self).__init__()
        # Encoder
        self.encoder1 = ResBlock(64)
        self.encoder2 = ResBlock(128)
        self.encoder3 = ResBlock(256)
        # Middle
        self.mism = MISM(256)
        self.dense = DenseBlock(256)
        # Decoder
        self.decoder1 = Conv2DTranspose(128, kernel size=2, strides=2,
padding='same')
        self.decoder2 = Conv2DTranspose(64, kernel_size=2, strides=2,
padding='same')
        self.final conv = Conv2D(1, kernel size=1, activation='sigmoid')
    def call(self, inputs):
        x1 = self.encoder1(inputs)
        x2 = self.encoder2(x1)
        x3 = self.encoder3(x2)
        x = self.mism(x3)
        x = self.dense(x)
        x = self.decoder1(x)
        x = self.decoder2(x)
        x = self.final_conv(x)
```

```
x = tf.image.resize(x, (128, 128))
      return x
class FRLoss(tf.keras.losses.Loss):
   def __init__(self, lambda_fr=5):
      super(FRLoss, self). init ()
      self.lambda_fr = lambda_fr
   def call(self, y_true, y_pred):
      intersection = tf.reduce_sum(y_true * y_pred)
      union = tf.reduce sum(y true) + tf.reduce sum(y pred)
      dice loss = 1 - (2 * intersection + 1e-7) / (union + 1e-7)
      ce_loss = tf.keras.losses.binary_crossentropy(y_true, y_pred)
      fr_loss = self.lambda_fr * tf.reduce_mean(tf.abs(y_true - y_pred))
      return dice_loss + ce_loss + fr_loss
model = HCMA UNet()
model.compile(optimizer=AdamW(learning_rate=1e-4), loss=FRLoss(),
metrics=['accuracy'])
model.compile(optimizer=AdamW(learning rate=1e-4), loss=FRLoss(),
metrics=['accuracy'])
history = model.fit(X_train, Y_train, validation_data=(X_val, Y_val),
batch_size=2, epochs=5)
Epoch 1/5
1.6959 - val accuracy: 0.9217 - val loss: 1.5210
Epoch 2/5
524/524 ---
                - val accuracy: 0.9294 - val loss: 1.4776
Epoch 3/5
- val accuracy: 0.9332 - val loss: 1.4426
Epoch 4/5
- val_accuracy: 0.9358 - val_loss: 1.2845
Epoch 5/5
524/524 ----
          86s 163ms/step - accuracy: 0.9355 - loss: 1.2903
- val accuracy: 0.9355 - val loss: 1.2605
loss = history.history['loss']
val_loss = history.history['val_loss']
accuracy = history.history['accuracy']
val accuracy = history.history['val accuracy']
```

```
epochs = range(1, len(loss) + 1)
plt.figure(figsize=(12, 5))
plt.subplot(1, 2, 1)
plt.plot(epochs, loss, 'b-', label='Training Loss')
plt.plot(epochs, val_loss, 'r-', label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training vs Validation Loss')
plt.legend()
plt.subplot(1, 2, 2)
plt.plot(epochs, accuracy, 'b-', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r-', label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training vs Validation Accuracy')
plt.legend()
plt.show()
             Training vs Validation Loss
                                                    Training vs Validation Accuracy
                                          0.936
                             Training Loss
                                                 Training Accuracy
  1.60
                             Validation Loss
                                                 Validation Accuracy
                                          0.934
  1.55
                                          0.932
  1.50
                                         0.930
```



from sklearn.metrics import confusion_matrix, classification_report
import seaborn as sns

```
y_pred_bin = (y_pred > 0.5).astype(np.uint8)

y_true_flat = Y_val.flatten().astype(np.uint8)

y_pred_flat = y_pred_bin.flatten()

cm = confusion_matrix(y_true_flat, y_pred_flat)

plt.figure(figsize=(6,5))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Background", "Object"], yticklabels=["Background", "Object"])

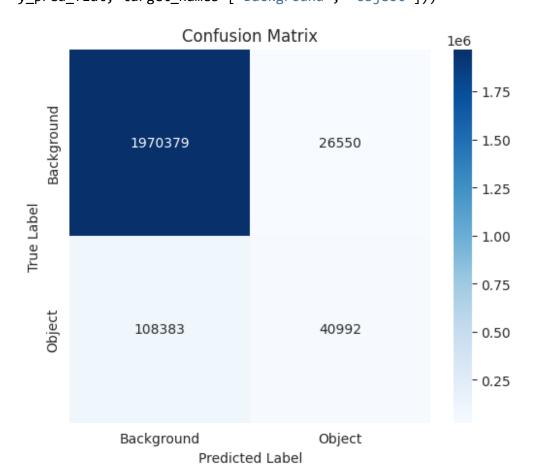
plt.xlabel('Predicted Label')

plt.ylabel('True Label')

plt.title('Confusion Matrix')

plt.show()

print("Classification Report:\n", classification_report(y_true_flat, y_pred_flat, target_names=["Background", "Object"]))
```



Classification Report:

	precision	recall	f1-score	support
Background	0.95	0.99	0.97	1996929

0bject	0.61	0.27	0.38	149375
accuracy macro avg weighted avg	0.78 0.92	0.63 0.94	0.94 0.67 0.93	2146304 2146304 2146304