

## Early Detection and Prediction of Brain Stroke Severity using Unet with Multihead Attention Mechanism



```
import numpy as np
import pandas as pd
import os

import matplotlib.pyplot as plt
from PIL import Image
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow.keras import layers, models

base_path = "/kaggle/input/inme-veri-seti-stroke-dataset/INME VERİ SETİ/YarismaVeriSeti_1_Oturum"
png_path = os.path.join(base_path, "PNG")
masks_path = os.path.join(base_path, "MASKS")
overlay_path = os.path.join(base_path, "OVERLAY")

import cv2

png_files = sorted(os.listdir(png_path))[:5]
mask_files = sorted(os.listdir(masks_path))[:5]
overlay_files = sorted(os.listdir(overlay_path))[:5]

fig, axes = plt.subplots(5, 3, figsize=(12, 15))

for i in range(5):

    img = cv2.imread(os.path.join(png_path, png_files[i]))
    mask = cv2.imread(os.path.join(masks_path, mask_files[i]),
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cv2.IMREAD_GRAYSCALE)
    overlay = cv2.imread(os.path.join(overlay_path, overlay_files[i]))

    img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
    overlay = cv2.cvtColor(overlay, cv2.COLOR_BGR2RGB)

    axes[i, 0].imshow(img)
    axes[i, 0].set_title("Original Image")
    axes[i, 0].axis("off")

    axes[i, 1].imshow(mask, cmap="gray")
    axes[i, 1].set_title("Mask")
    axes[i, 1].axis("off")

    axes[i, 2].imshow(overlay)
    axes[i, 2].set_title("Overlay")
    axes[i, 2].axis("off")

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

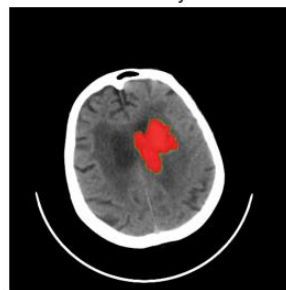
Original Image



Mask



Overlay



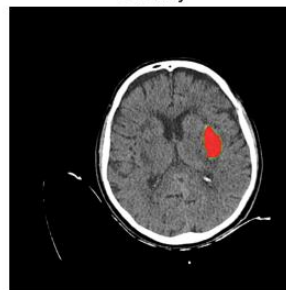
Original Image



Mask



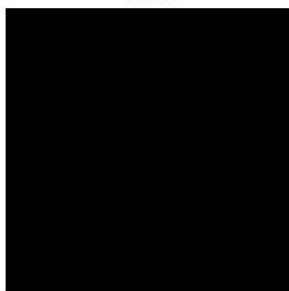
Overlay



Original Image



Mask



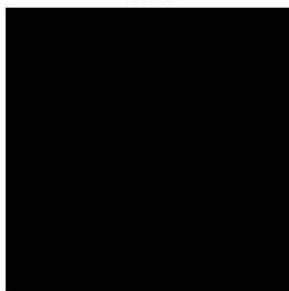
Overlay



Original Image



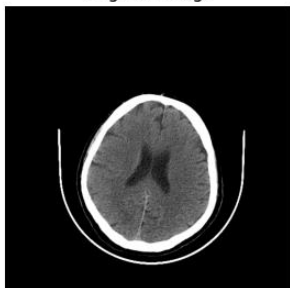
Mask



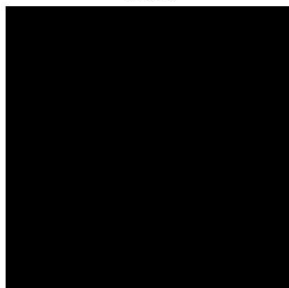
Overlay



Original Image



Mask



Overlay



```

def load_images_and_masks(image_folder, mask_folder, image_size=(256, 256)):
    images = []
    masks = []
    image_files = sorted(os.listdir(image_folder))
    mask_files = sorted(os.listdir(mask_folder))

    for img_file, mask_file in zip(image_files, mask_files):
        img_path = os.path.join(image_folder, img_file)
        mask_path = os.path.join(mask_folder, mask_file)

        img = Image.open(img_path).convert("L").resize(image_size)
        mask = Image.open(mask_path).convert("L").resize(image_size)

        img = np.array(img) / 255.0
        mask = np.array(mask) / 255.0

        images.append(np.expand_dims(img, axis=-1))
        masks.append(np.expand_dims(mask, axis=-1))

    return np.array(images), np.array(masks)

images, masks = load_images_and_masks(png_path, masks_path)

import tensorflow as tf

gpus = tf.config.list_physical_devices('GPU')
if gpus:
    try:
        for gpu in gpus:
            tf.config.experimental.set_memory_growth(gpu, True)
        print("GPUs Available:", gpus)
    except RuntimeError as e:
        print(e)
else:
    print("No GPU found. Running on CPU.")

GPUs Available: [PhysicalDevice(name='/physical_device:GPU:0',
device_type='GPU'), PhysicalDevice(name='/physical_device:GPU:1',
device_type='GPU')]

X_train, X_val, y_train, y_val = train_test_split(images, masks,
test_size=0.2, random_state=42)

def unet_model(input_size=(256, 256, 1)):
    inputs = tf.keras.Input(input_size)

    conv1 = layers.Conv2D(64, 3, activation="relu", padding="same")(inputs)
    conv1 = layers.Conv2D(64, 3, activation="relu", padding="same")(conv1)
    pool1 = layers.MaxPooling2D(pool_size=(2, 2))(conv1)

```

```

conv2 = layers.Conv2D(128, 3, activation="relu", padding="same")(pool1)
conv2 = layers.Conv2D(128, 3, activation="relu", padding="same")(conv2)
pool2 = layers.MaxPooling2D(pool_size=(2, 2))(conv2)

conv3 = layers.Conv2D(256, 3, activation="relu", padding="same")(pool2)
conv3 = layers.Conv2D(256, 3, activation="relu", padding="same")(conv3)

up1 = layers.UpSampling2D(size=(2, 2))(conv3)
concat1 = layers.concatenate([conv2, up1], axis=-1)
conv4 = layers.Conv2D(128, 3, activation="relu", padding="same")(concat1)
conv4 = layers.Conv2D(128, 3, activation="relu", padding="same")(conv4)

up2 = layers.UpSampling2D(size=(2, 2))(conv4)
concat2 = layers.concatenate([conv1, up2], axis=-1)
conv5 = layers.Conv2D(64, 3, activation="relu", padding="same")(concat2)
conv5 = layers.Conv2D(64, 3, activation="relu", padding="same")(conv5)

outputs = layers.Conv2D(1, 1, activation="sigmoid")(conv5)

model = models.Model(inputs, outputs)
return model

model = unet_model(input_size=(256, 256, 1))
model.compile(optimizer="adam", loss="binary_crossentropy",
metrics=["accuracy"])
model.summary()

```

Model: "functional\_2"

Layer (type) Connected to	Output Shape	Param #
input_layer_2 (InputLayer)	(None, 256, 256, 1)	0 -
conv2d_22 (Conv2D) input_layer_2[0][0]	(None, 256, 256, 64)	640
conv2d_23 (Conv2D) conv2d_22[0][0]	(None, 256, 256, 64)	36,928

max_pooling2d_4 conv2d_23[0][0] (MaxPooling2D)	(None, 128, 128, 64)	0
conv2d_24 (Conv2D) max_pooling2d_4[0][0]	(None, 128, 128, 128)	73,856
conv2d_25 (Conv2D) conv2d_24[0][0]	(None, 128, 128, 128)	147,584
max_pooling2d_5 conv2d_25[0][0] (MaxPooling2D)	(None, 64, 64, 128)	0
conv2d_26 (Conv2D) max_pooling2d_5[0][0]	(None, 64, 64, 256)	295,168
conv2d_27 (Conv2D) conv2d_26[0][0]	(None, 64, 64, 256)	590,080
up_sampling2d_4 conv2d_27[0][0] (UpSampling2D)	(None, 128, 128, 256)	0
concatenate_4 conv2d_25[0][0], (Concatenate) up_sampling2d_4[0][0]	(None, 128, 128, 384)	0
conv2d_28 (Conv2D) concatenate_4[0][0]	(None, 128, 128, 128)	442,496
conv2d_29 (Conv2D) conv2d_28[0][0]	(None, 128, 128, 128)	147,584
up_sampling2d_5 conv2d_29[0][0]	(None, 256, 256, 128)	0

(UpSampling2D)			
concatenate_5 conv2d_23[0][0], (Concatenate) up_sampling2d_5[0][0]	(None, 256, 256, 192)	0	
conv2d_30 (Conv2D) concatenate_5[0][0]	(None, 256, 256, 64)	110,656	
conv2d_31 (Conv2D) conv2d_30[0][0]	(None, 256, 256, 64)	36,928	
conv2d_32 (Conv2D) conv2d_31[0][0]	(None, 256, 256, 1)	65	

Total params: 1,881,985 (7.18 MB)

Trainable params: 1,881,985 (7.18 MB)

Non-trainable params: 0 (0.00 B)

```
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    batch_size=8,
    epochs=5,
    verbose=1
)
```

Epoch 1/5

20/20 ————— 11s 328ms/step - accuracy: 0.8792 - loss: 0.3010 -  
val\_accuracy: 0.9967 - val\_loss: 0.0078

Epoch 2/5

20/20 ————— 6s 297ms/step - accuracy: 0.9959 - loss: 0.0098 -  
val\_accuracy: 0.9967 - val\_loss: 0.0082

Epoch 3/5

20/20 ————— 6s 302ms/step - accuracy: 0.9955 - loss: 0.0076 -  
val\_accuracy: 0.9967 - val\_loss: 0.0070

Epoch 4/5

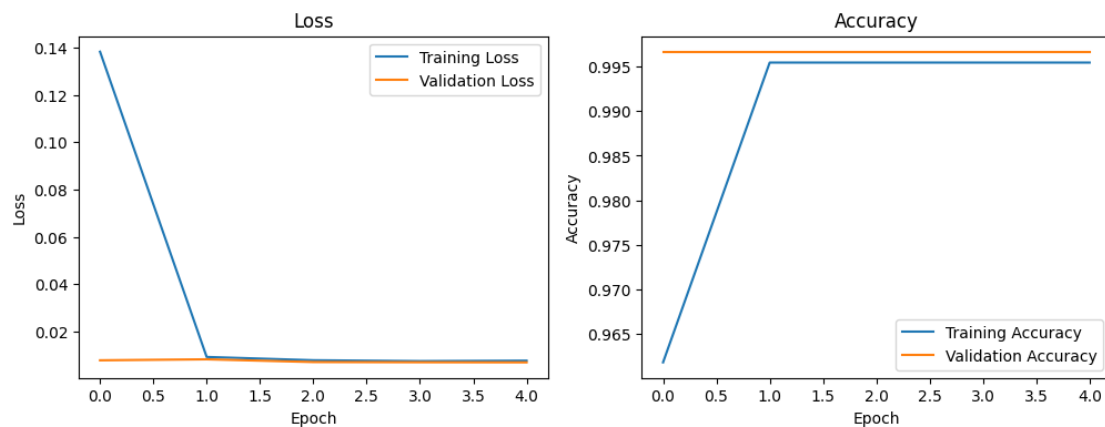
20/20 ————— 6s 307ms/step - accuracy: 0.9959 - loss: 0.0060 -  
val\_accuracy: 0.9967 - val\_loss: 0.0069

Epoch 5/5

20/20 ————— 6s 309ms/step - accuracy: 0.9958 - loss: 0.0070 -  
val\_accuracy: 0.9967 - val\_loss: 0.0069

```
def plot_training_history(history):  
    plt.figure(figsize=(12, 4))  
  
    plt.subplot(1, 2, 1)  
    plt.plot(history.history["loss"], label="Training Loss")  
    plt.plot(history.history["val_loss"], label="Validation Loss")  
    plt.title("Loss")  
    plt.xlabel("Epoch")  
    plt.ylabel("Loss")  
    plt.legend()  
  
    plt.subplot(1, 2, 2)  
    plt.plot(history.history["accuracy"], label="Training Accuracy")  
    plt.plot(history.history["val_accuracy"], label="Validation Accuracy")  
    plt.title("Accuracy")  
    plt.xlabel("Epoch")  
    plt.ylabel("Accuracy")  
    plt.legend()  
  
    plt.show()
```

plot\_training\_history(history)



```
def multihead_attention_block(inputs, key_dim, num_heads):  
    """Adds a multi-head attention block."""  
    attention = layers.MultiHeadAttention(num_heads=num_heads,  
key_dim=key_dim)(inputs, inputs)  
    attention = layers.LayerNormalization(epsilon=1e-6)(attention + inputs)  
    return attention  
  
def unet_model(input_size=(256, 256, 1)):  
    inputs = tf.keras.Input(input_size)
```



```

conv1 = layers.Conv2D(64, 3, activation="relu", padding="same")(inputs)
conv1 = layers.Conv2D(64, 3, activation="relu", padding="same")(conv1)
pool1 = layers.MaxPooling2D(pool_size=(2, 2))(conv1)

conv2 = layers.Conv2D(128, 3, activation="relu", padding="same")(pool1)
conv2 = layers.Conv2D(128, 3, activation="relu", padding="same")(conv2)
pool2 = layers.MaxPooling2D(pool_size=(2, 2))(conv2)

conv3 = layers.Conv2D(256, 3, activation="relu", padding="same")(pool2)
conv3 = layers.Conv2D(256, 3, activation="relu", padding="same")(conv3)

reshaped_conv3 = layers.Reshape((-1, 256))(conv3)
attention_conv3 = multihead_attention_block(reshaped_conv3,
key_dim=256//4, num_heads=4)
attention_conv3 = layers.Reshape((conv3.shape[1], conv3.shape[2],
256))(attention_conv3)

up1 = layers.UpSampling2D(size=(2, 2))(attention_conv3)
concat1 = layers.concatenate([conv2, up1], axis=-1)
conv4 = layers.Conv2D(128, 3, activation="relu", padding="same")(concat1)
conv4 = layers.Conv2D(128, 3, activation="relu", padding="same")(conv4)

up2 = layers.UpSampling2D(size=(2, 2))(conv4)
concat2 = layers.concatenate([conv1, up2], axis=-1)
conv5 = layers.Conv2D(64, 3, activation="relu", padding="same")(concat2)
conv5 = layers.Conv2D(64, 3, activation="relu", padding="same")(conv5)

outputs = layers.Conv2D(1, 1, activation="sigmoid")(conv5)

model = models.Model(inputs, outputs)
return model

model = unet_model(input_size=(256, 256, 1))
model.compile(optimizer="adam", loss="binary_crossentropy",
metrics=["accuracy"])
model.summary()

```

Model: "functional\_3"

Layer (type)	Output Shape	Param #
Connected to		
input_layer_3 (InputLayer)	(None, 256, 256, 1)	0 -

conv2d_33 (Conv2D) input_layer_3[0][0]	(None, 256, 256, 64)	640
conv2d_34 (Conv2D) conv2d_33[0][0]	(None, 256, 256, 64)	36,928
max_pooling2d_6 conv2d_34[0][0] (MaxPooling2D)	(None, 128, 128, 64)	0
conv2d_35 (Conv2D) max_pooling2d_6[0][0]	(None, 128, 128, 128)	73,856
conv2d_36 (Conv2D) conv2d_35[0][0]	(None, 128, 128, 128)	147,584
max_pooling2d_7 conv2d_36[0][0] (MaxPooling2D)	(None, 64, 64, 128)	0
conv2d_37 (Conv2D) max_pooling2d_7[0][0]	(None, 64, 64, 256)	295,168
conv2d_38 (Conv2D) conv2d_37[0][0]	(None, 64, 64, 256)	590,080
reshape_2 (Reshape) conv2d_38[0][0]	(None, 4096, 256)	0
multi_head_attention_1 reshape_2[0][0], (MultiHeadAttention) reshape_2[0][0]	(None, 4096, 256)	263,168
add_1 (Add) multi_head_attention_...	(None, 4096, 256)	0

reshape_2[0][0]			
layer_normalization_1 add_1[0][0] (LayerNormalization)	(None, 4096, 256)	512	
reshape_3 (Reshape) layer_normalization_1...	(None, 64, 64, 256)	0	
up_sampling2d_6 reshape_3[0][0] (UpSampling2D)	(None, 128, 128, 256)	0	
concatenate_6 conv2d_36[0][0], (Concatenate) up_sampling2d_6[0][0]	(None, 128, 128, 384)	0	
conv2d_39 (Conv2D) concatenate_6[0][0]	(None, 128, 128, 128)	442,496	
conv2d_40 (Conv2D) conv2d_39[0][0]	(None, 128, 128, 128)	147,584	
up_sampling2d_7 conv2d_40[0][0] (UpSampling2D)	(None, 256, 256, 128)	0	
concatenate_7 conv2d_34[0][0], (Concatenate) up_sampling2d_7[0][0]	(None, 256, 256, 192)	0	
conv2d_41 (Conv2D) concatenate_7[0][0]	(None, 256, 256, 64)	110,656	
conv2d_42 (Conv2D)	(None, 256, 256, 64)	36,928	

conv2d_41[0][0]			
conv2d_43 (Conv2D)	(None, 256, 256, 1)	65	
conv2d_42[0][0]			

Total params: 2,145,665 (8.19 MB)

Trainable params: 2,145,665 (8.19 MB)

Non-trainable params: 0 (0.00 B)

```
history = model.fit(
    X_train, y_train,
    validation_data=(X_val, y_val),
    batch_size=8,
    epochs=5,
    verbose=1
)
```

Epoch 1/5

20/20 ————— 19s 648ms/step - accuracy: 0.9924 - loss: 0.1135 -  
val\_accuracy: 0.9967 - val\_loss: 0.0085

Epoch 2/5

20/20 ————— 12s 607ms/step - accuracy: 0.9960 - loss: 0.0095 -  
val\_accuracy: 0.9967 - val\_loss: 0.0082

Epoch 3/5

20/20 ————— 12s 601ms/step - accuracy: 0.9963 - loss: 0.0070 -  
val\_accuracy: 0.9967 - val\_loss: 0.0087

Epoch 4/5

20/20 ————— 12s 597ms/step - accuracy: 0.9958 - loss: 0.0080 -  
val\_accuracy: 0.9967 - val\_loss: 0.0082

Epoch 5/5

20/20 ————— 12s 595ms/step - accuracy: 0.9969 - loss: 0.0066 -  
val\_accuracy: 0.9967 - val\_loss: 0.0075

```
def plot_training_history(history):
```

```
    plt.figure(figsize=(12, 4))
```

```
    plt.subplot(1, 2, 1)
```

```
    plt.plot(history.history["loss"], label="Training Loss")
```

```
    plt.plot(history.history["val_loss"], label="Validation Loss")
```

```
    plt.title("Loss")
```

```
    plt.xlabel("Epoch")
```

```
    plt.ylabel("Loss")
```

```
    plt.legend()
```

```
    plt.subplot(1, 2, 2)
```

```
    plt.plot(history.history["accuracy"], label="Training Accuracy")
```

```
plt.plot(history.history["val_accuracy"], label="Validation Accuracy")
plt.title("Accuracy")
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.legend()
```

```
plt.show()
```

```
plot_training_history(history)
```

