Sample code to proceed:

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# NeuroSentiment3: EEG + MRI from LEMON and Text from IMDB
# STEP 1: Load EEG, MRI from LEMON and Text from IMDB
lemon_eeg_dir = 'datasets/LEMON/EEG/' # Replace with your actual path
lemon_mri_dir = 'datasets/LEMON/MRI/' # Replace with your actual path
from datasets import load_dataset
# Load IMDB text data
imdb_dataset = load_dataset("imdb")
text data = imdb dataset['train']['text'][:1000] # Subset for efficiency
text_labels = imdb_dataset['train']['label'][:1000] # 0=neg, 1=pos
# STEP 2: Preprocessing EEG using MNE
import mne
import numpy as np
import os
def preprocess eeg(file path):
  raw = mne.io.read_raw_fif(file_path, preload=True)
  raw.filter(1., 40., fir_design='firwin')
  raw.set_eeg_reference('average', projection=True)
  epochs = mne.make fixed length epochs(raw, duration=2.0, preload=True)
  return epochs.get_data()
# STEP 3: Preprocessing MRI using NiBabel
import nibabel as nib
from nilearn.image import resample img
def preprocess mri(mri path):
  img = nib.load(mri path)
  target\_shape = (64, 64, 64)
  resampled = resample_img(img, target_affine=np.eye(3)*4, target_shape=target_shape)
  return resampled.get_fdata()
# STEP 4: Tokenize and Encode Text using BERT
from transformers import BertTokenizer, BertModel
import torch
tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
bert model = BertModel.from pretrained('bert-base-uncased')
def encode text(text list):
  inputs = tokenizer(text_list, return_tensors="pt", padding=True, truncation=True,
max length=128)
  with torch.no_grad():
    outputs = bert_model(**inputs)
  return outputs.last_hidden_state.mean(dim=1) # [B, 768]
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# STEP 5: Build Modality Encoders
import torch.nn as nn
class EEGEncoder(nn.Module):
  def __init__(self):
    super().__init__()
    self.lstm = nn.LSTM(input_size=64, hidden_size=128, batch_first=True)
  def forward(self, x):
    \_, (hn, \_) = self.lstm(x)
    return hn[-1]
class MRIEncoder(nn.Module):
  def __init__(self):
    super(). init ()
    self.conv = nn.Sequential(
       nn.Conv3d(1, 8, 3, padding=1), nn.ReLU(), nn.MaxPool3d(2),
       nn.Conv3d(8, 16, 3, padding=1), nn.ReLU(), nn.AdaptiveAvgPool3d(1)
  def forward(self, x):
    x = x.unsqueeze(1) # [B, 1, 64, 64, 64]
    x = self.conv(x)
    return x.view(x.size(0), -1)
# STEP 6: Fusion Model with Cross-Attention
class FusionModel(nn.Module):
  def __init__(self):
    super(). init ()
    self.eeg_encoder = EEGEncoder()
    self.mri_encoder = MRIEncoder()
    self.text_fc = nn.Linear(768, 128)
    self.attn = nn.MultiheadAttention(embed_dim=128, num_heads=4, batch_first=True)
    self.classifier = nn.Sequential(
       nn.Linear(384, 128), nn.ReLU(), nn.Linear(128, 3) # 3 classes: pos, neutral, neg
    )
  def forward(self, eeg, mri, text):
     eeg_feat = self.eeg_encoder(eeg) # [B, 128]
    mri feat = self.mri encoder(mri) # [B, 128]
    text feat = self.text fc(text) #[B, 128]
    eeg_attn, _ = self.attn(eeg_feat.unsqueeze(1), text_feat.unsqueeze(1), text_feat.unsqueeze(1))
    mri_attn, _ = self.attn(mri_feat.unsqueeze(1), text_feat.unsqueeze(1), text_feat.unsqueeze(1))
    combined = torch.cat([eeg_attn.squeeze(1), mri_attn.squeeze(1), text_feat], dim=1)
    return self.classifier(combined)
# STEP 7: Training and Evaluation
def train(model, data_loader, optimizer, loss_fn):
  model.train()
  for batch in data loader:
    eeg, mri, text, labels = batch
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preds = model(eeg, mri, text)
    loss = loss_fn(preds, labels)
    optimizer.zero_grad()
    loss.backward()
    optimizer.step()

# STEP 8: Usage Example (pseudo-code)
# eeg_data = [preprocess_eeg(os.path.join(lemon_eeg_dir, f)) for f in eeg_file_list]
# mri_data = [preprocess_mri(os.path.join(lemon_mri_dir, f)) for f in mri_file_list]
# text_encoded = encode_text(text_data)
# model = FusionModel()
# train(model, data_loader, optimizer, loss_fn)

# Note: You need to implement a DataLoader that returns (eeg_tensor, mri_tensor, text_tensor, label_tensor)
# where eeg_tensor.shape = [B, T, C], mri_tensor.shape = [B, 64, 64, 64], etc.
```