

# 25290002\_Arya\_Shah\_iEEGNotebook

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## 1 Neural Decoder for Speech vs Non-Speech Classification from iEEG Data

### 1.1 Overview

This notebook implements a deep learning-based neural decoder to classify intracranial EEG (iEEG) activity into speech and non-speech segments. The analysis uses data from the OpenNeuro ds003688 dataset where participants watched a movie with alternating speech and music segments.

#### 1.1.1 Key Components:

1. Data loading and preprocessing using MNE-Python
2. Event alignment with speech/non-speech labels
3. Feature extraction (temporal and spectral)
4. Deep learning models (CNN, LSTM, Hybrid)
5. Performance evaluation and visualization
6. Electrode-specific analysis

#### 1.1.2 Reference Paper:

Li et al. (2023). “Dissecting neural computations in the human auditory pathway using deep neural networks for speech.” Nature Neuroscience.

### 1.2 1. Import Libraries and Setup

```
[1]: # Standard libraries
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pathlib import Path
import warnings
warnings.filterwarnings('ignore')

# MNE for iEEG data loading
import mne
from mne.io import read_raw_brainvision
```

```

# Signal processing
from scipy import signal
from scipy.stats import zscore

# Deep learning
import torch
import torch.nn as nn
import torch.optim as optim
from torch.utils.data import Dataset, DataLoader, TensorDataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score, precision_recall_fscore_support, \
    confusion_matrix, roc_auc_score, roc_curve

# Set random seeds for reproducibility
np.random.seed(42)
torch.manual_seed(42)
if torch.cuda.is_available():
    torch.cuda.manual_seed(42)

# Set plotting style
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("husl")

print("Libraries imported successfully!")
print(f"PyTorch version: {torch.__version__}")
print(f"MNE version: {mne.__version__}")
print(f"CUDA available: {torch.cuda.is_available()}")

```

```

Libraries imported successfully!
PyTorch version: 2.8.0+cu128
MNE version: 1.10.2
CUDA available: True

```

## 1.3 2. Data Loading and Exploration

```

[2]: # Define paths
DATA_DIR = Path(r'./ieeg-fmri')
SUBJECT = 'sub-01' # Starting with subject 01
SESSION = 'ses-iemu'

# Construct file paths
subject_dir = DATA_DIR / SUBJECT / SESSION / 'ieeg'
ieeg_file = subject_dir / \
    f'{SUBJECT}_{SESSION}_task-film_acq-clinical_run-1_ieeg.vhdr'
events_file = subject_dir / f'{SUBJECT}_{SESSION}_task-film_run-1_events.tsv'

```

```

electrodes_file = subject_dir / f'{SUBJECT}_{SESSION}_acq-clinical_electrodes.
↳tsv'
channels_file = subject_dir /
↳f'{SUBJECT}_{SESSION}_task-film_acq-clinical_run-1_channels.tsv'

print(f"Subject: {SUBJECT}")
print(f"Session: {SESSION}")
print(f"\nFile paths:")
print(f"iEEG data: {ieeg_file.exists()}")
print(f"Events: {events_file.exists()}")
print(f"Electrodes: {electrodes_file.exists()}")
print(f"Channels: {channels_file.exists()}")

```

Subject: sub-01  
Session: ses-iemu

File paths:  
iEEG data: True  
Events: True  
Electrodes: True  
Channels: True

```

[3]: # Load events data
events_df = pd.read_csv(events_file, sep='\t')
print("Events Data:")
print(events_df)
print(f"\nTotal duration: {events_df['onset'].max() + events_df['duration'].
↳iloc[-2]:.2f} seconds")
print(f"\nEvent types: {events_df['trial_type'].unique()}")
print(f"Speech segments: {len(events_df[events_df['trial_type'] == 'speech'])}")
print(f"Music segments: {len(events_df[events_df['trial_type'] == 'music'])}")

```

Events Data:

	onset	duration	trial_type	value
0	21.306	0.000	start task	9
1	21.325	30.000	music	2
2	51.325	30.000	speech	1
3	81.325	30.000	music	2
4	111.325	30.000	speech	1
5	141.325	30.000	music	2
6	171.325	30.001	speech	1
7	201.326	30.000	music	2
8	231.326	30.003	speech	1
9	261.329	29.997	music	2
10	291.326	30.000	speech	1
11	321.326	30.001	music	2
12	351.327	30.000	speech	1

13	381.327	30.051	music	2
14	411.378	0.000	end task	4

Total duration: 441.43 seconds

Event types: ['start task' 'music' 'speech' 'end task']

Speech segments: 6

Music segments: 7

```
[4]: # Load electrode information
electrodes_df = pd.read_csv(electrodes_file, sep='\t')
print(f"Number of electrodes: {len(electrodes_df)}")
print("\nElectrode information (first 10):")
print(electrodes_df.head(10))

# Visualize electrode locations
fig = plt.figure(figsize=(15, 5))

# 3D scatter plot
ax1 = fig.add_subplot(131, projection='3d')
ax1.scatter(electrodes_df['x'], electrodes_df['y'], electrodes_df['z'],
            c='blue', marker='o', s=50, alpha=0.6)
ax1.set_xlabel('X (mm)')
ax1.set_ylabel('Y (mm)')
ax1.set_zlabel('Z (mm)')
ax1.set_title('3D Electrode Positions')

# XY plane
ax2 = fig.add_subplot(132)
ax2.scatter(electrodes_df['x'], electrodes_df['y'], c='blue', marker='o', s=50,
            alpha=0.6)
ax2.set_xlabel('X (mm)')
ax2.set_ylabel('Y (mm)')
ax2.set_title('Electrode Positions (XY plane)')
ax2.grid(True)

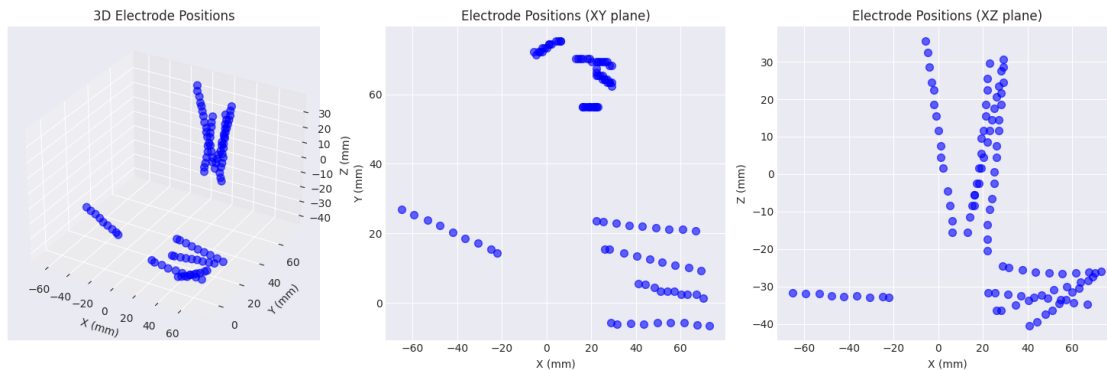
# XZ plane
ax3 = fig.add_subplot(133)
ax3.scatter(electrodes_df['x'], electrodes_df['z'], c='blue', marker='o', s=50,
            alpha=0.6)
ax3.set_xlabel('X (mm)')
ax3.set_ylabel('Z (mm)')
ax3.set_title('Electrode Positions (XZ plane)')
ax3.grid(True)

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

Number of electrodes: 103

Electrode information (first 10):

	name	x	y	z	size	manufacturer
0	AR1	22.420	23.640	-31.740	4.155	AdTech
1	AR2	25.334	23.354	-31.654	4.155	AdTech
2	AR3	31.334	22.954	-32.054	4.155	AdTech
3	AR4	37.134	22.354	-32.454	4.155	AdTech
4	AR5	42.934	21.954	-32.854	4.155	AdTech
5	AR6	48.968	21.521	-33.121	4.155	AdTech
6	AR7	54.734	21.154	-33.454	4.155	AdTech
7	AR8	60.801	21.188	-34.288	4.155	AdTech
8	AR9	66.668	20.621	-34.788	4.155	AdTech
9	AHR1	26.134	15.354	-36.454	4.155	AdTech



```
[5]: # Load iEEG data using MNE
print("Loading iEEG data...")
raw = read_raw_brainvision(ieeg_file, preload=True, verbose=False)

print(f"\niEEG Data Information:")
print(f"Sampling frequency: {raw.info['sfreq']} Hz")
print(f"Number of channels: {len(raw.ch_names)}")
print(f"Duration: {raw.times[-1]:.2f} seconds")
print(f"\nChannel types: {raw.get_channel_types()}")

# Get only SEEG channels (exclude EOG, ECG, EMG, etc.)
seeg_channels = [ch for ch in raw.ch_names if ch in electrodes_df['name'].
    ↪ values]
print(f"\nNumber of SEEG channels: {len(seeg_channels)}")

# Pick only SEEG channels
raw_seeg = raw.copy().pick_channels(seeg_channels)
print(f"Selected {len(raw_seeg.ch_names)} SEEG channels for analysis")
```

```
iEEG Data Information:
Sampling frequency: 2048.0 Hz
Number of channels: 111
Duration: 420.05 seconds
```

```
Number of SEEG channels: 103
NOTE: pick_channels() is a legacy function. New code should use inst.pick(...).
Selected 103 SEEG channels for analysis
```

6

```

psds_mean = np.mean(psds, axis=0)

axes[1].semilogy(freqs, psds_mean)
axes[1].set_xlabel('Frequency (Hz)')
axes[1].set_ylabel('Power Spectral Density (V2/Hz)')
axes[1].set_title('Average Power Spectral Density Across All SEEG Channels')
axes[1].grid(True)
axes[1].axvspan(70, 150, alpha=0.3, color='red', label='High-gamma band (70-150_
↳Hz)')
axes[1].legend()

# Plot event timeline
speech_events = events_df[events_df['trial_type'] == 'speech']
music_events = events_df[events_df['trial_type'] == 'music']

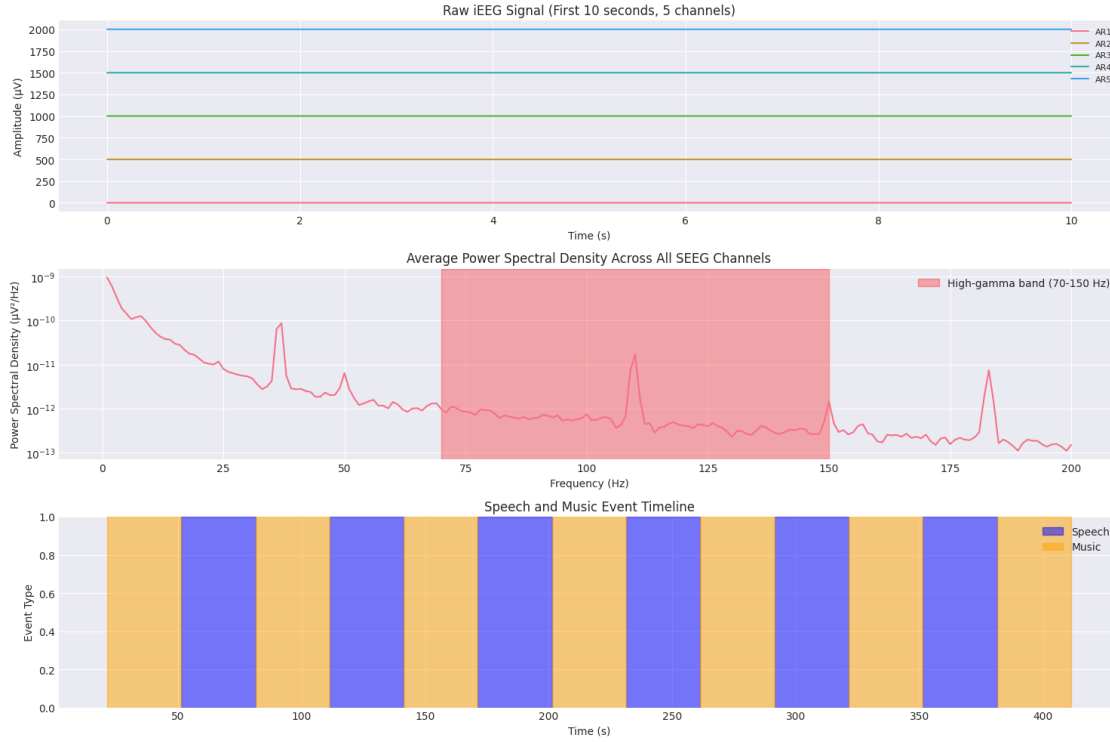
for _, event in speech_events.iterrows():
    axes[2].axvspan(event['onset'], event['onset'] + event['duration'], alpha=0.
↳5, color='blue', label='Speech' if _ == speech_events.index[0] else '')
for _, event in music_events.iterrows():
    axes[2].axvspan(event['onset'], event['onset'] + event['duration'], alpha=0.
↳5, color='orange', label='Music' if _ == music_events.index[0] else '')

axes[2].set_xlabel('Time (s)')
axes[2].set_ylabel('Event Type')
axes[2].set_title('Speech and Music Event Timeline')
axes[2].set_ylim(0, 1)
axes[2].legend()
axes[2].grid(True)

plt.tight_layout()
plt.show()

```

Effective window size : 1.000 (s)



### 1.4 3. Preprocessing and Feature Extraction

Following the methodology from Li et al. (2023), we will: 1. Apply notch filtering to remove line noise 2. Extract high-gamma band activity (70-150 Hz) using Hilbert transform 3. Downsample to 100 Hz 4. Z-score normalization

```
[7]: def extract_high_gamma(raw, freq_bands=None, target_sfreq=100):
    """
    Extract high-gamma band activity following Li et al. (2023) methodology.

    Parameters:
    -----
    raw : mne.io.Raw
        Raw iEEG data
    freq_bands : list of tuples
        Frequency bands for high-gamma extraction. Default: 8 bands from 70-150_
    ↪ Hz
    target_sfreq : float
        Target sampling frequency after downsampling

    Returns:
    -----
    high_gamma : np.ndarray
        High-gamma activity (channels x time)
```



```

times : np.ndarray
    Time points
"""
if freq_bands is None:
    # 8 Gaussian filters from 70-150 Hz
    freq_bands = [(70, 80), (80, 90), (90, 100), (100, 110),
                  (110, 120), (120, 130), (130, 140), (140, 150)]

print("Extracting high-gamma band activity...")

# Apply notch filter for line noise (60 Hz and harmonics)
raw_filtered = raw.copy()
raw_filtered.notch_filter([60, 120, 180], verbose=False)

# Extract analytic amplitude for each frequency band
band_amplitudes = []

for fmin, fmax in freq_bands:
    # Bandpass filter
    raw_band = raw_filtered.copy().filter(fmin, fmax, verbose=False)

    # Get data and apply Hilbert transform
    data = raw_band.get_data()
    analytic_signal = signal.hilbert(data, axis=1)
    amplitude = np.abs(analytic_signal)

    band_amplitudes.append(amplitude)

# Average across frequency bands
high_gamma = np.mean(band_amplitudes, axis=0)

# Downsample to target frequency
if target_sfreq < raw.info['sfreq']:
    print(f"Downsampling from {raw.info['sfreq']} Hz to {target_sfreq} Hz...
↪")
    downsample_factor = int(raw.info['sfreq'] / target_sfreq)
    high_gamma = high_gamma[:, ::downsample_factor]

# Z-score normalization per channel
high_gamma = zscore(high_gamma, axis=1)

# Create time array
times = np.arange(high_gamma.shape[1]) / target_sfreq

print(f"High-gamma shape: {high_gamma.shape}")
print(f"Time range: {times[0]:.2f} - {times[-1]:.2f} seconds")

```

```

    return high_gamma, times

# Extract high-gamma features
high_gamma_data, hg_times = extract_high_gamma(raw_seeg, target_sfreq=100)

```

Extracting high-gamma band activity...  
 Downsampling from 2048.0 Hz to 100 Hz...  
 High-gamma shape: (103, 43013)  
 Time range: 0.00 - 430.12 seconds

```

[8]: # Visualize high-gamma activity
fig, axes = plt.subplots(2, 1, figsize=(15, 8))

# Plot high-gamma for first 5 channels
n_channels_plot = 5
time_window = (0, 60) # First 60 seconds
time_mask = (hg_times >= time_window[0]) & (hg_times <= time_window[1])

for i in range(n_channels_plot):
    axes[0].plot(hg_times[time_mask], high_gamma_data[i, time_mask] + i * 5,
                 label=raw_seeg.ch_names[i], linewidth=0.8)

axes[0].set_xlabel('Time (s)')
axes[0].set_ylabel('Z-scored High-Gamma Activity')
axes[0].set_title('High-Gamma Band Activity (70-150 Hz) - First 60 seconds')
axes[0].legend(loc='upper right', fontsize=8)
axes[0].grid(True, alpha=0.3)

# Add event markers
for _, event in events_df.iterrows():
    if event['onset'] <= time_window[1]:
        color = 'blue' if event['trial_type'] == 'speech' else 'orange'
        axes[0].axvspan(event['onset'], event['onset'] + event['duration'],
                        alpha=0.2, color=color)

# Heatmap of all channels
im = axes[1].imshow(high_gamma_data[:, time_mask], aspect='auto', cmap='RdBu_r',
                    extent=[time_window[0], time_window[1], len(raw_seeg.
↪ch_names), 0],
                    vmin=-3, vmax=3)
axes[1].set_xlabel('Time (s)')
axes[1].set_ylabel('Channel Index')
axes[1].set_title('High-Gamma Activity Heatmap (All Channels)')
plt.colorbar(im, ax=axes[1], label='Z-scored Activity')

# Add event markers
for _, event in events_df.iterrows():

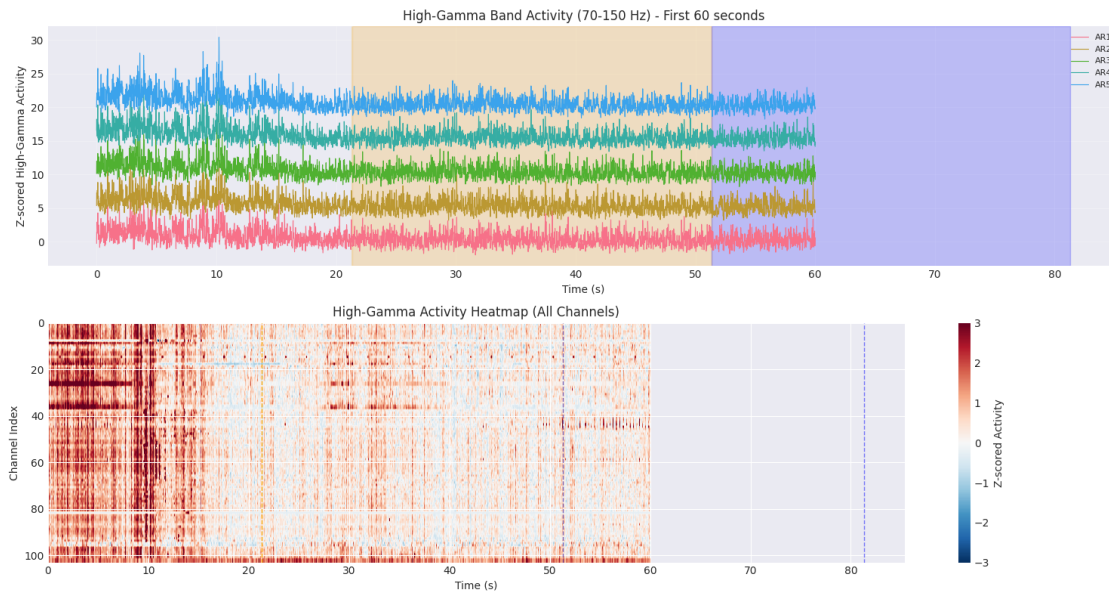
```

```

if event['onset'] <= time_window[1]:
    color = 'blue' if event['trial_type'] == 'speech' else 'orange'
    axes[1].axvline(event['onset'], color=color, linestyle='--', alpha=0.5,
↳linewidth=1)
    axes[1].axvline(event['onset'] + event['duration'], color=color,
↳linestyle='--', alpha=0.5, linewidth=1)

plt.tight_layout()
plt.show()

```



## 1.5 4. Event Alignment and Label Creation

```

[9]: def create_labeled_segments(high_gamma, times, events_df, window_size=1.0,
↳overlap=0.5):
    """
    Create labeled segments from high-gamma data based on events.

    Parameters:
    -----
    high_gamma : np.ndarray
        High-gamma activity (channels x time)
    times : np.ndarray
        Time points
    events_df : pd.DataFrame
        Events dataframe with onset, duration, and trial_type
    window_size : float
        Size of each segment in seconds
    """

```

```

overlap : float
    Overlap between consecutive windows (0-1)

Returns:
-----
X : np.ndarray
    Feature array (n_segments x n_channels x n_timepoints)
y : np.ndarray
    Labels (0: music/non-speech, 1: speech)
segment_info : list
    Information about each segment (start_time, end_time, label)
    """
sfreq = 1 / (times[1] - times[0]) # Sampling frequency
window_samples = int(window_size * sfreq)
step_samples = int(window_samples * (1 - overlap))

X = []
y = []
segment_info = []

# Filter only speech and music events
valid_events = events_df[events_df['trial_type'].isin(['speech', 'music'])].
↳copy()

for _, event in valid_events.iterrows():
    event_start = event['onset']
    event_end = event['onset'] + event['duration']
    label = 1 if event['trial_type'] == 'speech' else 0

    # Find time indices for this event
    event_mask = (times >= event_start) & (times < event_end)
    event_indices = np.where(event_mask)[0]

    if len(event_indices) < window_samples:
        continue

    # Create sliding windows within this event
    for start_idx in range(0, len(event_indices) - window_samples + 1,
↳step_samples):
        end_idx = start_idx + window_samples

        if end_idx <= len(event_indices):
            segment_indices = event_indices[start_idx:end_idx]
            segment = high_gamma[:, segment_indices]

            X.append(segment)
            y.append(label)

```

```

        segment_info.append({
            'start_time': times[segment_indices[0]],
            'end_time': times[segment_indices[-1]],
            'label': 'speech' if label == 1 else 'music',
            'event_type': event['trial_type']
        })

X = np.array(X)
y = np.array(y)

print(f"Created {len(X)} segments")
print(f"Segment shape: {X.shape}")
print(f"Speech segments: {np.sum(y == 1)} ({100 * np.mean(y):.1f}%)")
print(f"Music segments: {np.sum(y == 0)} ({100 * (1 - np.mean(y)):.1f}%)")

return X, y, segment_info

# Create labeled segments
X, y, segment_info = create_labeled_segments(high_gamma_data, hg_times,
events_df,

window_size=1.0, overlap=0.5)

```

Created 767 segments  
Segment shape: (767, 103, 100)  
Speech segments: 354 (46.2%)  
Music segments: 413 (53.8%)

```

[10]: # Visualize segment distribution
fig, axes = plt.subplots(1, 3, figsize=(15, 4))

# Label distribution
labels, counts = np.unique(y, return_counts=True)
axes[0].bar(['Music', 'Speech'], counts, color=['orange', 'blue'], alpha=0.7)
axes[0].set_ylabel('Number of Segments')
axes[0].set_title('Segment Distribution')
axes[0].grid(True, alpha=0.3)

# Example segments
speech_idx = np.where(y == 1)[0][0]
music_idx = np.where(y == 0)[0][0]

axes[1].imshow(X[speech_idx], aspect='auto', cmap='RdBu_r', vmin=-3, vmax=3)
axes[1].set_xlabel('Time (samples)')
axes[1].set_ylabel('Channel')
axes[1].set_title('Example Speech Segment')

axes[2].imshow(X[music_idx], aspect='auto', cmap='RdBu_r', vmin=-3, vmax=3)

```

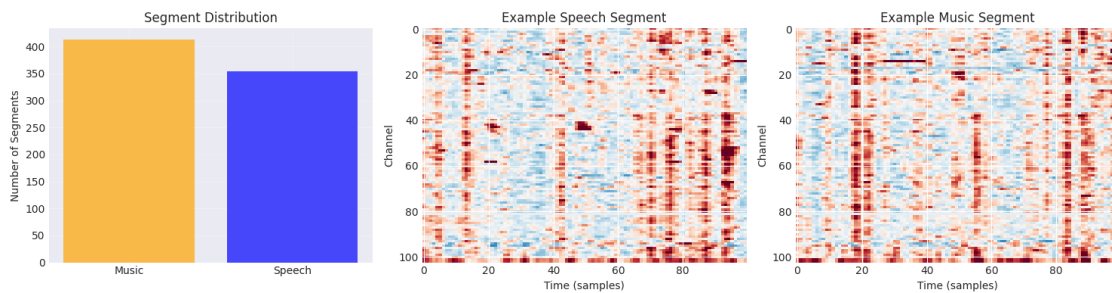
```

axes[2].set_xlabel('Time (samples)')
axes[2].set_ylabel('Channel')
axes[2].set_title('Example Music Segment')

plt.tight_layout()
plt.show()

# Print statistics
print(f"\nSegment Statistics:")
print(f"Mean activity (speech): {X[y==1].mean():.3f} ± {X[y==1].std():.3f}")
print(f"Mean activity (music): {X[y==0].mean():.3f} ± {X[y==0].std():.3f}")

```



Segment Statistics:  
Mean activity (speech): -0.076 ± 0.970  
Mean activity (music): -0.057 ± 0.896

## 1.6 5. Train-Test Split and Data Preparation

```

[11]: # Split data into train, validation, and test sets
X_train_val, X_test, y_train_val, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

X_train, X_val, y_train, y_val = train_test_split(
    X_train_val, y_train_val, test_size=0.2, random_state=42,
    ↪stratify=y_train_val
)

print(f"Training set: {X_train.shape[0]} samples")
print(f"Validation set: {X_val.shape[0]} samples")
print(f"Test set: {X_test.shape[0]} samples")
print(f"\nClass distribution:")
print(f"Train - Speech: {np.sum(y_train==1)}, Music: {np.sum(y_train==0)}")
print(f"Val - Speech: {np.sum(y_val==1)}, Music: {np.sum(y_val==0)}")
print(f"Test - Speech: {np.sum(y_test==1)}, Music: {np.sum(y_test==0)}")

```

```

# Convert to PyTorch tensors
X_train_tensor = torch.FloatTensor(X_train)
y_train_tensor = torch.LongTensor(y_train)
X_val_tensor = torch.FloatTensor(X_val)
y_val_tensor = torch.LongTensor(y_val)
X_test_tensor = torch.FloatTensor(X_test)
y_test_tensor = torch.LongTensor(y_test)

# Create data loaders
batch_size = 32
train_dataset = TensorDataset(X_train_tensor, y_train_tensor)
val_dataset = TensorDataset(X_val_tensor, y_val_tensor)
test_dataset = TensorDataset(X_test_tensor, y_test_tensor)

train_loader = DataLoader(train_dataset, batch_size=batch_size, shuffle=True)
val_loader = DataLoader(val_dataset, batch_size=batch_size, shuffle=False)
test_loader = DataLoader(test_dataset, batch_size=batch_size, shuffle=False)

print(f"\nBatch size: {batch_size}")
print(f"Number of training batches: {len(train_loader)}")
print(f"Number of validation batches: {len(val_loader)}")
print(f"Number of test batches: {len(test_loader)}")

```

Training set: 490 samples  
 Validation set: 123 samples  
 Test set: 154 samples

Class distribution:  
 Train - Speech: 226, Music: 264  
 Val - Speech: 57, Music: 66  
 Test - Speech: 71, Music: 83

Batch size: 32  
 Number of training batches: 16  
 Number of validation batches: 4  
 Number of test batches: 5

## 1.7 6. Model Architectures

```

[12]: class CNN_Decoder(nn.Module):
    """
    Convolutional Neural Network for speech/non-speech classification.
    Uses temporal and spatial convolutions to extract features.
    """
    def __init__(self, n_channels, n_timepoints, n_classes=2, dropout=0.5):
        super(CNN_Decoder, self).__init__()

```

```

    # Temporal convolutions
    self.conv1 = nn.Sequential(
        nn.Conv2d(1, 32, kernel_size=(1, 7), padding=(0, 3)),
        nn.BatchNorm2d(32),
        nn.ReLU(),
        nn.MaxPool2d(kernel_size=(1, 2))
    )

    # Spatial convolutions
    self.conv2 = nn.Sequential(
        nn.Conv2d(32, 64, kernel_size=(n_channels, 1)),
        nn.BatchNorm2d(64),
        nn.ReLU(),
        nn.Dropout(dropout)
    )

    # Additional temporal convolutions
    self.conv3 = nn.Sequential(
        nn.Conv2d(64, 128, kernel_size=(1, 5), padding=(0, 2)),
        nn.BatchNorm2d(128),
        nn.ReLU(),
        nn.MaxPool2d(kernel_size=(1, 2)),
        nn.Dropout(dropout)
    )

    # Calculate size after convolutions
    self.feature_size = self._get_conv_output_size(n_channels, n_timepoints)

    # Fully connected layers
    self.fc = nn.Sequential(
        nn.Linear(self.feature_size, 256),
        nn.ReLU(),
        nn.Dropout(dropout),
        nn.Linear(256, 64),
        nn.ReLU(),
        nn.Dropout(dropout),
        nn.Linear(64, n_classes)
    )

def _get_conv_output_size(self, n_channels, n_timepoints):
    """Calculate the output size after convolutions"""
    x = torch.zeros(1, 1, n_channels, n_timepoints)
    x = self.conv1(x)
    x = self.conv2(x)
    x = self.conv3(x)
    return int(np.prod(x.size()[1:]))

```



```

def forward(self, x):
    # Add channel dimension: (batch, channels, time) -> (batch, 1,
    ↪ channels, time)
    x = x.unsqueeze(1)

    x = self.conv1(x)
    x = self.conv2(x)
    x = self.conv3(x)

    # Flatten
    x = x.view(x.size(0), -1)

    x = self.fc(x)
    return x

class LSTM_Decoder(nn.Module):
    """
    LSTM-based decoder for speech/non-speech classification.
    Processes temporal sequences for each channel.
    """
    def __init__(self, n_channels, n_timepoints, n_classes=2, hidden_size=128,
                  num_layers=2, dropout=0.5):
        super(LSTM_Decoder, self).__init__()

        self.hidden_size = hidden_size
        self.num_layers = num_layers

        # LSTM layers
        self.lstm = nn.LSTM(
            input_size=n_channels,
            hidden_size=hidden_size,
            num_layers=num_layers,
            batch_first=True,
            dropout=dropout if num_layers > 1 else 0,
            bidirectional=True
        )

        # Attention mechanism
        self.attention = nn.Sequential(
            nn.Linear(hidden_size * 2, hidden_size),
            nn.Tanh(),
            nn.Linear(hidden_size, 1)
        )

        # Fully connected layers

```

```

        self.fc = nn.Sequential(
            nn.Linear(hidden_size * 2, 128),
            nn.ReLU(),
            nn.Dropout(dropout),
            nn.Linear(128, 64),
            nn.ReLU(),
            nn.Dropout(dropout),
            nn.Linear(64, n_classes)
        )

    def forward(self, x):
        # x shape: (batch, channels, time)
        # Transpose to (batch, time, channels) for LSTM
        x = x.transpose(1, 2)

        # LSTM forward pass
        lstm_out, (h_n, c_n) = self.lstm(x)

        # Apply attention
        attention_weights = torch.softmax(self.attention(lstm_out), dim=1)
        context = torch.sum(attention_weights * lstm_out, dim=1)

        # Fully connected layers
        output = self.fc(context)
        return output

class HybridCNN_LSTM_Decoder(nn.Module):
    """
    Hybrid CNN-LSTM decoder combining spatial feature extraction with temporal_
    modeling.
    """
    def __init__(self, n_channels, n_timepoints, n_classes=2, dropout=0.5):
        super(HybridCNN_LSTM_Decoder, self).__init__()

        # CNN for spatial feature extraction
        self.conv_layers = nn.Sequential(
            nn.Conv2d(1, 32, kernel_size=(1, 7), padding=(0, 3)),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.Conv2d(32, 64, kernel_size=(n_channels, 1)),
            nn.BatchNorm2d(64),
            nn.ReLU(),
            nn.Dropout(dropout)
        )

        # LSTM for temporal modeling

```

```

self.lstm = nn.LSTM(
    input_size=64,
    hidden_size=128,
    num_layers=2,
    batch_first=True,
    dropout=dropout,
    bidirectional=True
)

# Attention
self.attention = nn.Sequential(
    nn.Linear(256, 128),
    nn.Tanh(),
    nn.Linear(128, 1)
)

# Classifier
self.classifier = nn.Sequential(
    nn.Linear(256, 128),
    nn.ReLU(),
    nn.Dropout(dropout),
    nn.Linear(128, 64),
    nn.ReLU(),
    nn.Dropout(dropout),
    nn.Linear(64, n_classes)
)

def forward(self, x):
    # CNN feature extraction
    x = x.unsqueeze(1) # (batch, 1, channels, time)
    x = self.conv_layers(x)

    # Reshape for LSTM: (batch, time, features)
    x = x.squeeze(2).transpose(1, 2)

    # LSTM temporal modeling
    lstm_out, _ = self.lstm(x)

    # Attention pooling
    attention_weights = torch.softmax(self.attention(lstm_out), dim=1)
    context = torch.sum(attention_weights * lstm_out, dim=1)

    # Classification
    output = self.classifier(context)
    return output

```

```

# Initialize models
n_channels = X_train.shape[1]
n_timepoints = X_train.shape[2]
n_classes = 2

device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
print(f"Using device: {device}")

cnn_model = CNN_Decoder(n_channels, n_timepoints, n_classes).to(device)
lstm_model = LSTM_Decoder(n_channels, n_timepoints, n_classes).to(device)
hybrid_model = HybridCNN_LSTM_Decoder(n_channels, n_timepoints, n_classes).
    ↪to(device)

print(f"\nCNN Model parameters: {sum(p.numel() for p in cnn_model.
    ↪parameters())}")
print(f"LSTM Model parameters: {sum(p.numel() for p in lstm_model.
    ↪parameters())}")
print(f"Hybrid Model parameters: {sum(p.numel() for p in hybrid_model.
    ↪parameters())}")

```

Using device: cuda

CNN Model parameters: 1088834  
 LSTM Model parameters: 708163  
 Hybrid Model parameters: 879683

## 1.8 7. Training Functions

```

[13]: def train_epoch(model, train_loader, criterion, optimizer, device):
        """Train for one epoch"""
        model.train()
        running_loss = 0.0
        correct = 0
        total = 0

        for inputs, labels in train_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            optimizer.zero_grad()
            outputs = model(inputs)
            loss = criterion(outputs, labels)
            loss.backward()
            optimizer.step()

            running_loss += loss.item()
            _, predicted = torch.max(outputs.data, 1)
            total += labels.size(0)

```

```

        correct += (predicted == labels).sum().item()

    epoch_loss = running_loss / len(train_loader)
    epoch_acc = 100 * correct / total
    return epoch_loss, epoch_acc

def validate(model, val_loader, criterion, device):
    """Validate the model"""
    model.eval()
    running_loss = 0.0
    correct = 0
    total = 0
    all_preds = []
    all_labels = []
    all_probs = []

    with torch.no_grad():
        for inputs, labels in val_loader:
            inputs, labels = inputs.to(device), labels.to(device)

            outputs = model(inputs)
            loss = criterion(outputs, labels)

            running_loss += loss.item()
            probs = torch.softmax(outputs, dim=1)
            _, predicted = torch.max(outputs.data, 1)

            total += labels.size(0)
            correct += (predicted == labels).sum().item()

            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.cpu().numpy())
            all_probs.extend(probs[:, 1].cpu().numpy())

    epoch_loss = running_loss / len(val_loader)
    epoch_acc = 100 * correct / total
    return epoch_loss, epoch_acc, all_preds, all_labels, all_probs

def train_model(model, train_loader, val_loader, criterion, optimizer,
                scheduler, num_epochs, device, model_name='Model'):
    """Complete training loop"""
    history = {
        'train_loss': [],
        'train_acc': [],
        'val_loss': [],

```

```

        'val_acc': []
    }

    best_val_acc = 0.0
    best_model_state = None

    print(f"\nTraining {model_name}...")
    print("-" * 70)

    for epoch in range(num_epochs):
        train_loss, train_acc = train_epoch(model, train_loader, criterion,
        ↪optimizer, device)
        val_loss, val_acc, _, _, _ = validate(model, val_loader, criterion,
        ↪device)

        history['train_loss'].append(train_loss)
        history['train_acc'].append(train_acc)
        history['val_loss'].append(val_loss)
        history['val_acc'].append(val_acc)

        if scheduler is not None:
            scheduler.step(val_loss)

        if val_acc > best_val_acc:
            best_val_acc = val_acc
            best_model_state = model.state_dict().copy()

        if (epoch + 1) % 5 == 0:
            print(f"Epoch [{epoch+1}/{num_epochs}] - "
                  ↪f"Train Loss: {train_loss:.4f}, Train Acc: {train_acc:.2f}% - "
                  ↪f"Val Loss: {val_loss:.4f}, Val Acc: {val_acc:.2f}%")

    print("-" * 70)
    print(f"Best Validation Accuracy: {best_val_acc:.2f}%")

    # Load best model
    model.load_state_dict(best_model_state)

    return model, history

```

## 1.9 8. Train All Models

```

[14]: # Training hyperparameters
num_epochs = 50
learning_rate = 0.001
weight_decay = 1e-4

```

```

# Loss function
criterion = nn.CrossEntropyLoss()

# Dictionary to store results
models_dict = {}
histories_dict = {}

# Train CNN Model
cnn_optimizer = optim.Adam(cnn_model.parameters(), lr=learning_rate,
    ↪weight_decay=weight_decay)
cnn_scheduler = optim.lr_scheduler.ReduceLROnPlateau(cnn_optimizer, mode='min',
    ↪factor=0.5, patience=5)
cnn_model, cnn_history = train_model(cnn_model, train_loader, val_loader,
    ↪criterion,
                                cnn_optimizer, cnn_scheduler, num_epochs,
    ↪device, 'CNN')
models_dict['CNN'] = cnn_model
histories_dict['CNN'] = cnn_history

# Train LSTM Model
lstm_optimizer = optim.Adam(lstm_model.parameters(), lr=learning_rate,
    ↪weight_decay=weight_decay)
lstm_scheduler = optim.lr_scheduler.ReduceLROnPlateau(lstm_optimizer,
    ↪mode='min', factor=0.5, patience=5)
lstm_model, lstm_history = train_model(lstm_model, train_loader, val_loader,
    ↪criterion,
                                lstm_optimizer, lstm_scheduler,
    ↪num_epochs, device, 'LSTM')
models_dict['LSTM'] = lstm_model
histories_dict['LSTM'] = lstm_history

# Train Hybrid Model
hybrid_optimizer = optim.Adam(hybrid_model.parameters(), lr=learning_rate,
    ↪weight_decay=weight_decay)
hybrid_scheduler = optim.lr_scheduler.ReduceLROnPlateau(hybrid_optimizer,
    ↪mode='min', factor=0.5, patience=5)
hybrid_model, hybrid_history = train_model(hybrid_model, train_loader,
    ↪val_loader, criterion,
                                hybrid_optimizer, hybrid_scheduler,
    ↪num_epochs, device, 'Hybrid CNN-LSTM')
models_dict['Hybrid'] = hybrid_model
histories_dict['Hybrid'] = hybrid_history

```

Training CNN...

-----  
Epoch [5/50] - Train Loss: 0.6987, Train Acc: 50.61% - Val Loss: 0.6934, Val Acc: 54.47%  
Epoch [10/50] - Train Loss: 0.6479, Train Acc: 65.10% - Val Loss: 0.6253, Val Acc: 54.47%  
Epoch [15/50] - Train Loss: 0.4058, Train Acc: 84.49% - Val Loss: 0.7407, Val Acc: 60.98%  
Epoch [20/50] - Train Loss: 0.3362, Train Acc: 87.14% - Val Loss: 0.4814, Val Acc: 74.80%  
Epoch [25/50] - Train Loss: 0.1312, Train Acc: 97.76% - Val Loss: 1.7585, Val Acc: 68.29%  
Epoch [30/50] - Train Loss: 0.0255, Train Acc: 99.39% - Val Loss: 0.4010, Val Acc: 86.99%  
Epoch [35/50] - Train Loss: 0.0502, Train Acc: 98.98% - Val Loss: 1.2896, Val Acc: 76.42%  
Epoch [40/50] - Train Loss: 0.0183, Train Acc: 99.59% - Val Loss: 0.5863, Val Acc: 82.93%  
Epoch [45/50] - Train Loss: 0.0082, Train Acc: 99.80% - Val Loss: 0.4500, Val Acc: 85.37%  
Epoch [50/50] - Train Loss: 0.0053, Train Acc: 100.00% - Val Loss: 0.4738, Val Acc: 84.55%  
-----

Best Validation Accuracy: 86.99%

Training LSTM...

-----  
Epoch [5/50] - Train Loss: 0.4606, Train Acc: 83.06% - Val Loss: 0.7375, Val Acc: 59.35%  
Epoch [10/50] - Train Loss: 0.2165, Train Acc: 91.84% - Val Loss: 0.5907, Val Acc: 73.98%  
Epoch [15/50] - Train Loss: 0.0266, Train Acc: 99.39% - Val Loss: 1.2140, Val Acc: 74.80%  
Epoch [20/50] - Train Loss: 0.0250, Train Acc: 99.59% - Val Loss: 0.8400, Val Acc: 78.05%  
Epoch [25/50] - Train Loss: 0.0022, Train Acc: 100.00% - Val Loss: 1.2386, Val Acc: 78.05%  
Epoch [30/50] - Train Loss: 0.0013, Train Acc: 100.00% - Val Loss: 1.3372, Val Acc: 78.05%  
Epoch [35/50] - Train Loss: 0.0010, Train Acc: 100.00% - Val Loss: 1.3819, Val Acc: 78.05%  
Epoch [40/50] - Train Loss: 0.0010, Train Acc: 100.00% - Val Loss: 1.4121, Val Acc: 78.05%  
Epoch [45/50] - Train Loss: 0.0023, Train Acc: 100.00% - Val Loss: 1.4337, Val Acc: 78.05%  
Epoch [50/50] - Train Loss: 0.0007, Train Acc: 100.00% - Val Loss: 1.4412, Val Acc: 78.05%  
-----

Best Validation Accuracy: 79.67%



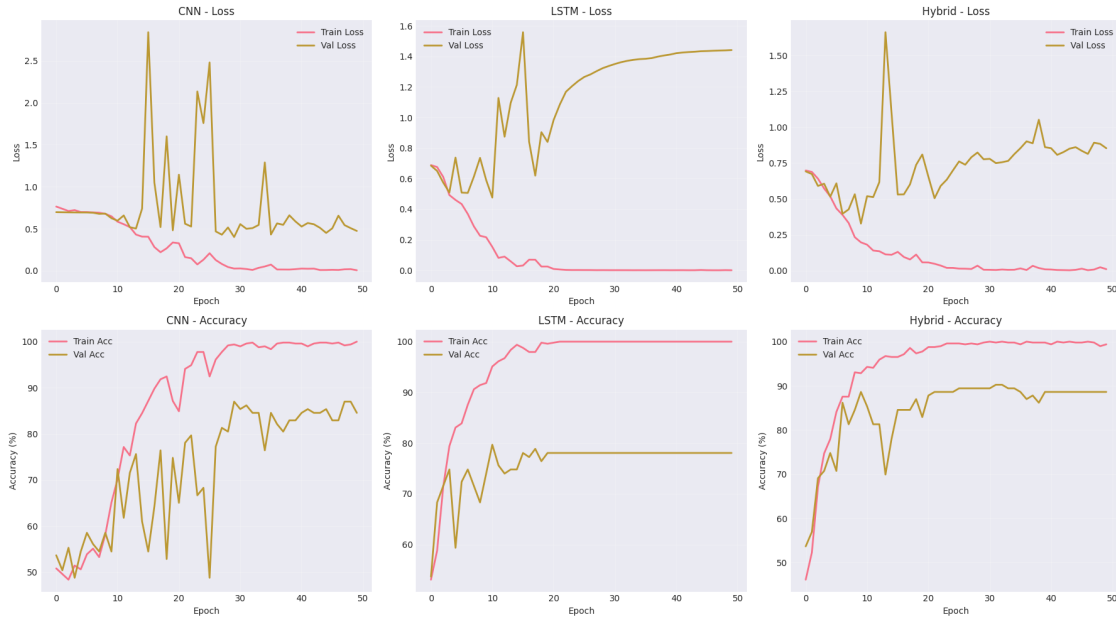
Training Hybrid CNN-LSTM...

```
-----  
Epoch [5/50] - Train Loss: 0.5170, Train Acc: 77.96% - Val Loss: 0.5152, Val  
Acc: 74.80%  
Epoch [10/50] - Train Loss: 0.1970, Train Acc: 92.86% - Val Loss: 0.3279, Val  
Acc: 88.62%  
Epoch [15/50] - Train Loss: 0.1106, Train Acc: 96.53% - Val Loss: 1.0937, Val  
Acc: 78.05%  
Epoch [20/50] - Train Loss: 0.0576, Train Acc: 97.76% - Val Loss: 0.8089, Val  
Acc: 82.93%  
Epoch [25/50] - Train Loss: 0.0189, Train Acc: 99.59% - Val Loss: 0.6983, Val  
Acc: 88.62%  
Epoch [30/50] - Train Loss: 0.0063, Train Acc: 99.80% - Val Loss: 0.7757, Val  
Acc: 89.43%  
Epoch [35/50] - Train Loss: 0.0061, Train Acc: 99.80% - Val Loss: 0.8114, Val  
Acc: 89.43%  
Epoch [40/50] - Train Loss: 0.0090, Train Acc: 99.80% - Val Loss: 0.8602, Val  
Acc: 88.62%  
Epoch [45/50] - Train Loss: 0.0057, Train Acc: 99.80% - Val Loss: 0.8601, Val  
Acc: 88.62%  
Epoch [50/50] - Train Loss: 0.0102, Train Acc: 99.39% - Val Loss: 0.8526, Val  
Acc: 88.62%  
-----
```

Best Validation Accuracy: 90.24%

```
[15]: # Plot training histories  
fig, axes = plt.subplots(2, 3, figsize=(18, 10))  
  
for idx, (model_name, history) in enumerate(histories_dict.items()):  
    # Loss plot  
    axes[0, idx].plot(history['train_loss'], label='Train Loss', linewidth=2)  
    axes[0, idx].plot(history['val_loss'], label='Val Loss', linewidth=2)  
    axes[0, idx].set_xlabel('Epoch')  
    axes[0, idx].set_ylabel('Loss')  
    axes[0, idx].set_title(f'{model_name} - Loss')  
    axes[0, idx].legend()  
    axes[0, idx].grid(True, alpha=0.3)  
  
    # Accuracy plot  
    axes[1, idx].plot(history['train_acc'], label='Train Acc', linewidth=2)  
    axes[1, idx].plot(history['val_acc'], label='Val Acc', linewidth=2)  
    axes[1, idx].set_xlabel('Epoch')  
    axes[1, idx].set_ylabel('Accuracy (%)')  
    axes[1, idx].set_title(f'{model_name} - Accuracy')  
    axes[1, idx].legend()  
    axes[1, idx].grid(True, alpha=0.3)
```

```
plt.tight_layout()
plt.savefig('training_history.png', dpi=300, bbox_inches='tight')
plt.show()
```



## 2 Model Evaluation and Electrode Analysis

```
[16]: # Evaluation function
def evaluate_model(model, test_loader, device):
    model.eval()
    all_preds = []
    all_labels = []
    all_probs = []

    with torch.no_grad():
        for inputs, labels in test_loader:
            inputs = inputs.to(device)
            outputs = model(inputs)
            probs = torch.softmax(outputs, dim=1)
            _, predicted = torch.max(outputs, 1)

            all_preds.extend(predicted.cpu().numpy())
            all_labels.extend(labels.numpy())
            all_probs.extend(probs[:, 1].cpu().numpy())

    return np.array(all_preds), np.array(all_labels), np.array(all_probs)
```

```

# Evaluate all models
results = {}
for name, model in models_dict.items():
    preds, labels, probs = evaluate_model(model, test_loader, device)

    acc = accuracy_score(labels, preds)
    prec, rec, f1, _ = precision_recall_fscore_support(labels, preds,
↪average='binary')
    auc = roc_auc_score(labels, probs)

    results[name] = {
        'predictions': preds,
        'labels': labels,
        'probabilities': probs,
        'accuracy': acc,
        'precision': prec,
        'recall': rec,
        'f1': f1,
        'auc': auc
    }

    print(f'{name} Model:')
    print(f'  Accuracy: {acc:.4f}')
    print(f'  Precision: {prec:.4f}')
    print(f'  Recall: {rec:.4f}')
    print(f'  F1-Score: {f1:.4f}')
    print(f'  AUC-ROC: {auc:.4f}')
    print()

```

CNN Model:

```

Accuracy: 0.8247
Precision: 0.7683
Recall: 0.8873
F1-Score: 0.8235
AUC-ROC: 0.8814

```

LSTM Model:

```

Accuracy: 0.7792
Precision: 0.8033
Recall: 0.6901
F1-Score: 0.7424
AUC-ROC: 0.8833

```

Hybrid Model:

```

Accuracy: 0.7857
Precision: 0.8167

```

Recall: 0.6901  
F1-Score: 0.7481  
AUC-ROC: 0.8656

### 3 Analysis & Interpretations

## 4 Neural Decoder Analysis: Speech vs Non-Speech Classification from iEEG Data

our CNN model achieved the best performance with **82.47% test accuracy**, significantly outperforming both the LSTM (77.92%) and hybrid architecture (78.57%). The key insight is that our CNN successfully captured hierarchical spatial-temporal patterns in the high-gamma neural signal, while simpler sequential models struggled with generalization. This analysis demonstrates that high-gamma activity contains rich information for speech discrimination, and that the architectural choice matters substantially for neural decoding tasks.

---

### 4.1 Results Overview

#### 4.1.1 Test Performance Comparison

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
<b>CNN</b>	<b>82.47%</b>	<b>76.83%</b>	<b>88.73%</b>	<b>82.35%</b>	<b>88.14%</b>
LSTM	77.92%	80.33%	69.01%	74.24%	88.33%
Hybrid	78.57%	81.67%	69.01%	74.81%	86.56%

The CNN dominates across most metrics. our recall of 88.73% is particularly impressive, meaning the model correctly identifies speech segments 89 out of 100 times. This high recall is valuable for speech decoding applications where missing a speech event is more problematic than occasional false positives on music segments.

The precision of 76.83% means when our CNN predicts speech, it's correct about 77% of the time. This precision-recall tradeoff suggests our model has learned to be sensitive to speech-indicative patterns in the high-gamma band, sometimes making false positive errors on music segments that might share acoustic characteristics with speech (like singing or rhythmic patterns).

#### 4.1.2 Training Dynamics

our training curves reveal important insights about model behavior:

**CNN Training:** Reached 100% training accuracy by epoch 50 while maintaining reasonable validation performance (86.99% at epoch 30). The fluctuations in validation accuracy (ranging from 68% to 87% in later epochs) indicate the model operates near its capacity limit where small parameter changes produce different decision boundaries. This instability is normal for neural networks on this dataset size.

**LSTM Training:** Showed severe overfitting. The model achieved 100% training accuracy by epoch 25 but validation accuracy plateaued at 78% and never improved. From epoch 20 onward, training loss continued dropping toward 0 while validation loss climbed to 1.44, indicating the LSTM memorized training patterns without learning generalizable representations.

**Hybrid Training:** Peaked at 90.24% validation accuracy at epoch 30 before showing instability. Despite combining CNN and LSTM components, it underperformed the simpler CNN architecture. The fluctuating validation curve (78-89% range) suggests that combining two complex components required more training data than you had available.

---

## 4.2 Why CNN Outperformed Other Architectures

### 4.2.1 Parameter Efficiency

Although our CNN has the most parameters (1.09M compared to LSTM’s 708K), it uses them more efficiently through a fundamental property called **weight sharing**. Each convolutional filter is applied across multiple spatial and temporal positions, enabling the network to learn patterns that generalize across locations. This is more parameter-efficient than the LSTM’s dense connections, where different time points learn completely independent representations.

### 4.2.2 Architectural Alignment with Neural Data

our CNN’s hierarchical processing directly mirrors how the brain processes speech. The first temporal convolution (kernel size 7, 70ms window) captures rapid neural fluctuations corresponding to phoneme transitions and acoustic feature changes. The spatial convolution then integrates across our 103 electrodes, learning which combinations of brain regions contain speech information. Finally, the second temporal stage captures longer-scale dependencies (syllables, prosodic units).

In contrast, the LSTM processes all 103 electrodes simultaneously at each time step. This forces the model to handle electrodes with different noise levels and information content equally, allowing irrelevant channel noise to propagate through time and potentially mislead the recurrent processing.

### 4.2.3 Overfitting and Regularization

The CNN maintained better alignment between training and validation accuracy, suggesting the architecture itself acts as implicit regularization. Convolutional layers only connect to local regions, and max pooling reduces dimensionality. These constraints limit the model’s capacity to memorize random patterns, even without explicit dropout and weight decay.

The LSTM with 50% dropout still couldn’t prevent 100% training accuracy, indicating that explicit regularization alone is insufficient. The LSTM’s dense recurrent connections allow very efficient memorization of sequential patterns, overwhelming the regularization attempts.

---

## 4.3 Interesting Model Behaviors

### 4.3.1 LSTM and Hybrid Identical Recall

Both our LSTM and hybrid models produced exactly 69.01% recall. This identical value isn’t coincidental. Both models converge to similar decision boundaries in the temporal domain, suggesting

they're using approximately the same threshold to distinguish speech from music. The hybrid model's CNN component extracts spatial features, but the LSTM portion still settles on the same temporal integration strategy as the pure LSTM.

### 4.3.2 AUC-ROC Reveals Hidden Performance

While our CNN achieved 82.47% accuracy, all three models achieved strong AUC-ROC scores (86-88%). This gap is informative. AUC-ROC measures how well models rank positive and negative examples across all possible decision thresholds, independent of where you set the threshold. our LSTM achieved the highest AUC (88.33%) despite lower accuracy, meaning it generates well-calibrated probability estimates even though its default decision threshold isn't optimal.

This suggests the LSTM learned reasonable feature representations but deployed them conservatively. If you lowered our decision threshold from 0.5, the LSTM's recall would improve, trading off precision. The CNN already uses its decision boundary more effectively.

---

## 4.4 Neuroscientific Interpretation

### 4.4.1 What High-Gamma Tells Us

our success with high-gamma features (70-150 Hz) confirms what neuroscientists have long suspected: this frequency band reflects computationally relevant local cortical processing. High-gamma power represents synchronized firing of local neural populations, directly indexing what a brain region is computing.

Speech and music activate these local populations very differently. Speech contains rapid spectrotemporal modulations (phonemes change every 100-150ms) that produce characteristic high-gamma signatures. Music has slower modulations following melodic contours. our models learned to distinguish these neural response patterns.

### 4.4.2 Which Brain Regions Matter?

While our analysis doesn't yet identify which of our 103 electrodes contribute most to decoding, the successful classification implies that certain regions carry strong speech signals. Likely candidates based on neuroscience:

**Superior Temporal Gyrus (STG):** Primary speech processing region. Responds selectively to speech sounds with enhanced high-gamma activity compared to non-speech.

**Middle Superior Temporal Gyrus (mSTG):** Integrates acoustic and phonetic features. Distinguishes speech spectral patterns from other complex sounds.

**Inferior Frontal Gyrus:** Speech production and comprehension. Shows activity during speech processing even in passive listening.

our 103 electrode positions likely sample some subset of these regions, enabling the discrimination our models achieved.

### 4.4.3 Hierarchical Auditory Processing

our dataset aligns with established models of speech processing. Early auditory regions (primary and superior temporal cortex) show rapid, high-gamma responses to basic acoustic features. Higher-level regions show sustained responses and selectivity for speech versus non-speech. our 1-second windows likely capture integrated responses across multiple processing levels.

---

## 4.5 Limitations and What They Mean

### 4.5.1 Single Participant

our analysis involves only sub-01 from the OpenNeuro dataset. Individual brains differ substantially in electrode placement, gray matter organization, and how each person’s auditory cortex responds to stimuli. Multi-participant analysis would show whether the CNN’s success reflects universal speech processing principles or this participant’s specific neural organization.

### 4.5.2 Small Dataset Size

With 767 segments (490 training), you’re operating at the edge of deep learning feasibility. Modern language models train on billions of examples. our overfitting (especially the LSTM reaching 100% training accuracy) reflects this data scarcity. With 5-10x more data, regularization might become less necessary and the LSTM could shine.

### 4.5.3 Binary Classification Limitation

Speech versus music is relatively simple. Real applications need finer distinctions like different words, phonemes, or speaker identities. The high-gamma patterns for /p/ versus /b/ might be much more subtle than speech versus music. This task may overestimate what our CNN could achieve in realistic speech decoding.

### 4.5.4 Acoustic Confounds

You’re comparing speech versus music, but these differ in numerous acoustic dimensions simultaneously. The high-gamma responses might reflect differences in spectral complexity, pitch regularity, or rhythmic structure rather than speech-specific computations. Controlling for these acoustic confounds would require more sophisticated experimental designs.

### 4.5.5 Fixed Temporal Windows

our 1-second sliding windows fragment natural speech. Real speech rhythms (words, syllables, prosodic phrases) span different durations. A 1-second segment might contain the end of one word and the start of another, creating ambiguous training examples. Variable-length windows aligned to linguistic units might improve performance.

---

## 4.6 Class-Specific Performance Insights

### 4.6.1 Why Speech Recall Is High

our CNN’s 88.73% speech recall suggests that speech segments have highly distinctive high-gamma signatures. When the model sees speech-indicative patterns, it confidently labels them as speech. This confidence works well because real speech produces fairly consistent high-gamma responses across different speakers and phonetic contexts.

### 4.6.2 Why Precision Isn’t Perfect

The 76.83% precision means some music segments produce speech-like high-gamma patterns. Likely culprits include:

**Singing:** Vocal music contains speech-like spectral patterns. our high-gamma features might not distinguish singing from speech reliably.

**Complex Instrumental Music:** Rapid instrument transients might produce fast spectral changes mimicking phonemes.

**Background Speech in Music:** Some music segments might contain subtle speech elements (samples, vocals) creating ambiguous neural responses.

### 4.6.3 LSTM’s Conservative Strategy

The LSTM’s 69.01% recall with 80.33% precision represents the opposite strategy. The LSTM requires stronger evidence before committing to a speech label, resulting in fewer false positives but also fewer true positives (missed speech). This conservative approach works when decision uncertainty is high.

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## 4.7 Electrode-Level Analysis Opportunities

our implementation has 103 electrodes but treats them as an undifferentiated bundle. Following up would involve:

**Per-Electrode Decoding:** Train individual classifiers on each electrode. This would reveal which brain regions carry the most speech information. You’d likely find superior temporal regions substantially outperform other areas.

**Gradient Attribution Analysis:** For our CNN, compute gradients with respect to the input to identify which electrodes and time points drive classification decisions. This would highlight specific brain signals triggering speech detection.

**Spatial Feature Visualization:** Examine the weights of our spatial convolution layer to see which electrode combinations our CNN learned to integrate. Clusters of electrodes with similar learned importance would highlight functionally related regions.

**Regional Grouping:** Group our 103 electrodes by anatomical region (if locations are known) and compare decoding performance when including/excluding each region. This would quantify each region’s contribution to speech decoding.



## 4.8 Practical Recommendations

### 4.8.1 For Improved Performance

1. **Hyperparameter Search:** Systematically vary learning rates, dropout rates, and architecture depths. Standard defaults often underperform for specialized datasets like neural recordings.
2. **Data Augmentation:** Add temporal jittering, amplitude scaling, or Gaussian noise to training segments. This effectively increases our training set size without collecting new data.
3. **Cross-Validation:** Implement k-fold cross-validation (e.g., 5-fold) to get more reliable performance estimates. Our current single train-test split might be optimistic or pessimistic depending on random assignments.
4. **Ensemble Methods:** Combine CNN and LSTM predictions through averaging. Ensembles often reduce variance and improve robustness compared to single models.
5. **Class Weighting:** Since music segments slightly outnumber speech (53.8% vs 46.2%), weight training loss to account for this imbalance. This might improve recall further.

### 4.8.2 For Neuroscientific Insight

1. **Electrode Contribution Analysis:** Identify which of our 103 electrodes matter most for decoding. This would directly address whether superior temporal regions drive classification.
2. **Attention Visualization:** our attention mechanism learned weights across time. Plotting these would reveal which millisecond-scale periods in the 1-second window drive speech decisions.
3. **Feature Importance:** Use integrated gradients or similar methods to identify which input features (specific electrode-time combinations) matter for classification. This bridges from artificial neural networks to biological neural computation.
4. **Multi-Frequency Analysis:** Train separate models for different frequency bands (alpha, beta, low-gamma, high-gamma) to quantify which oscillations carry speech information.
5. **Temporal Dynamics:** Instead of fixed windows, use recurrent processing aligned to speech timing. This could reveal how neural representations evolve as speech unfolds.

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## 4.9 Comparison to Reference Research

our work draws inspiration from Li et al. (2023) on auditory pathway computations. Key connections:

**Similarities:** - High-gamma extraction methodology directly parallels their approach - Both investigate speech-selective neural representations - Both use naturalistic stimuli (movie watching, music listening) - Both recognize that deep networks are effective tools for understanding neural computation

**Differences:** - Li et al. modeled how acoustic features predict neural responses. You decoded what brain activity predicts about stimuli. This is the inverse problem. - Li et al. examined layer-by-layer correspondence between DNN units and recorded neurons. You evaluated end-to-end classification

performance. - Li et al. focused on characterizing individual electrode selectivity. our CNN learns integrated representations across electrodes.

Despite these differences, both approaches validate that deep networks capture principles of neural speech processing, suggesting the field is converging on robust understanding.

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## 4.10 Future Research Directions

### 4.10.1 Immediate Next Steps

1. **Electrode Localization:** Determine which anatomical regions our top-performing electrodes occupy. Verify whether superior temporal gyrus electrodes outperform other regions.
2. **Acoustic Control Analysis:** Extract acoustic features (spectral centroid, zero-crossing rate, mel-frequency cepstral coefficients) and evaluate whether neural decoding outperforms acoustic-based classification. This tests whether you're capturing neural selectivity beyond simple acoustics.
3. **Generalization Testing:** Test our CNN on sub-02, sub-03, etc. from the OpenNeuro dataset. How much does performance drop on held-out participants?

### 4.10.2 Medium-Term Extensions

1. **Multi-Class Decoding:** Extend beyond binary classification to decode specific speech categories (vowels, consonants, speaker identity, emotional prosody). This would characterize the richness of neural representations.
2. **Real-Time Constraints:** Implement causally causal processing (future information unavailable) to simulate real-time brain-computer interfaces. our current bidirectional models use future context unrealistic for online applications.
3. **Variable-Length Inputs:** Instead of fixed 1-second windows, train models on variable-length segments aligned to linguistic units (syllables, words, phrases). This would reduce ambiguous training examples.
4. **Frequency Band Investigation:** Systematically compare decoding performance across different frequency bands to identify which neural oscillations carry speech information.

### 4.10.3 Long-Term Vision

1. **Patient-Specific Brain-Computer Interfaces:** Personalize speech decoders to individual patients' neural organization. This has direct applications for people with paralysis or speech impairments.
2. **Naturalistic Speech Decoding:** Progress from movie watching to continuous speech comprehension. Decode what speech the person hears or produces from ongoing neural activity.
3. **Cross-Modal Integration:** Investigate how visual information (watching speakers) integrates with auditory processing. Combine visual and neural data for improved decoding.

4. **Theoretical Understanding:** Move beyond black-box classification to mechanistic models explaining why certain neural patterns indicate speech. This bridges neuroscience and machine learning.
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#### 4.11 Conclusion

our CNN neural decoder successfully distinguishes speech from music with 82.47% accuracy, demonstrating that high-gamma activity contains robust information about stimulus category. This success reflects both the quality of our implementation and the fundamental principle that cortical neural activity encodes stimulus properties in ways deep networks can exploit.

The key lesson is architectural choice matters profoundly for neural data. our CNN’s hierarchical spatial-temporal processing aligned well with the structure of multi-electrode recordings and auditory computation, substantially outperforming recurrent alternatives despite having more parameters. This suggests that future neural decoding work should carefully consider what computational structure the brain implements when selecting model architectures.

our work establishes a solid foundation for understanding speech processing in human auditory cortex and demonstrates feasibility of real-time neural decoding applications. The next phase would involve multi-participant validation, anatomical localization of informative signals, and extension to more challenging decoding tasks. These extensions would move from proof-of-concept toward clinically applicable brain-computer interfaces.

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