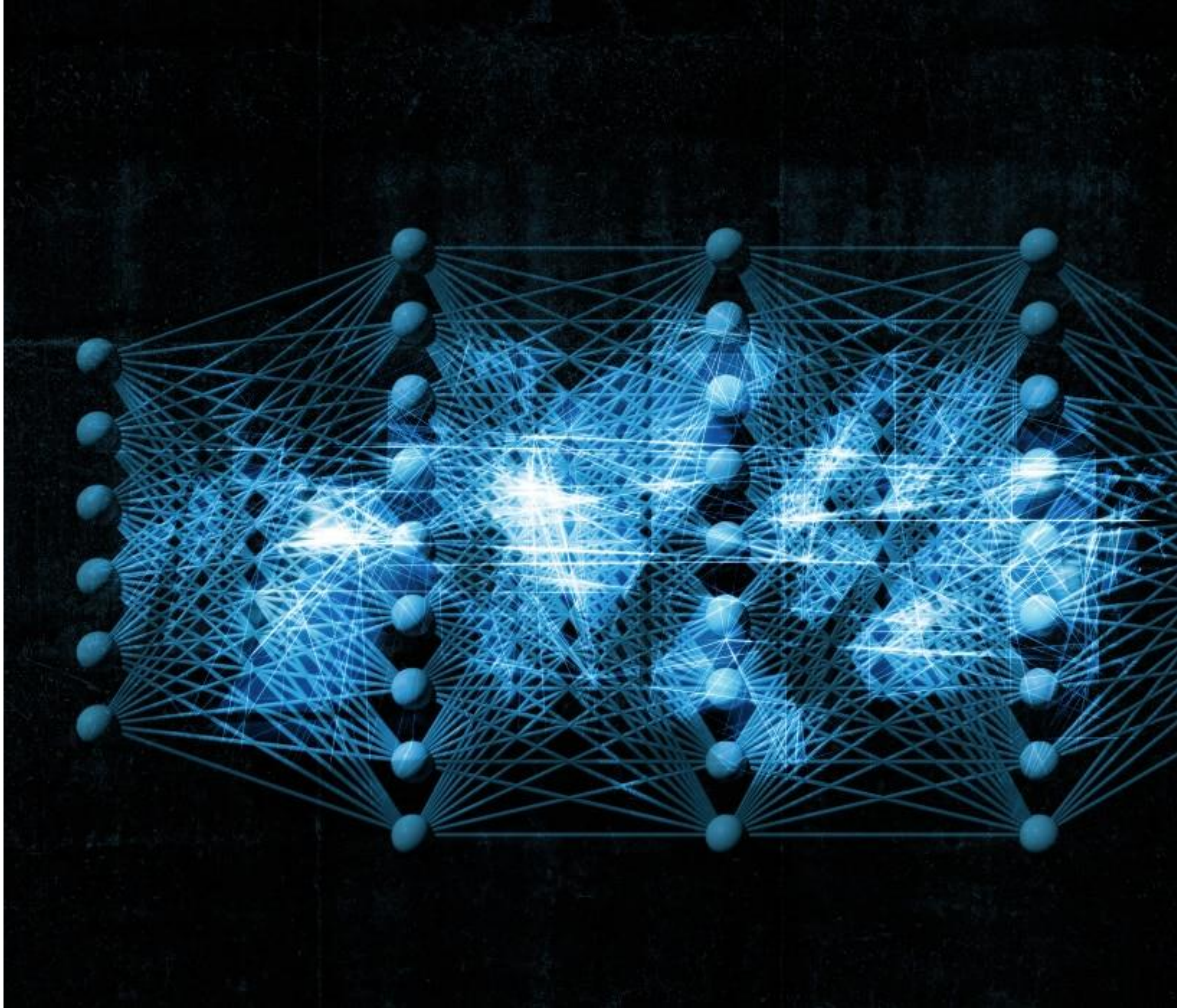
EEG Emotion Classification using Deep Learning



Presented by ***Kimi Doan***
CU Boulder 2025

About me

Kimi Doan

Chief Innovation Officer, Earable Neuroscience

Kimi leads innovation at Earable Neuroscience, a 3x CES Innovation Awards winner (2023-2025) pioneering AI wearables and digital therapeutics based on brainwave technology.

Background & Expertise

- 15+ years in global tech leadership across marketing, business development, and strategic partnerships
- Tech Evangelist and Business Connector with deep expertise in computer science and neuroscience
- Former Global Chief Marketing Officer at VinFast EV (NASDAQ: VFS, 2020-2022)

Education

- MSc in Computer Science, University of Colorado Boulder (Expected Graduation 2026)
- MBA (First-Class Honours), University of Gloucestershire, UK, 2011
- BSc in Computer Science and Telecommunications, Helsinki University of Technology, 2010

Research Interests

Applied AI and neuroscience therapy approach to enhance longevity and unlock human potential.

Agenda

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Introduction & Problem Statement

Understanding the challenge and why deep learning matters

02

Exploratory Data Analysis

SEED-IV dataset structure, feature extraction, and key insights

03

Methodology

Deep learning models and evaluation strategy

04

Results & Discussion

Performance comparison, findings, and future directions

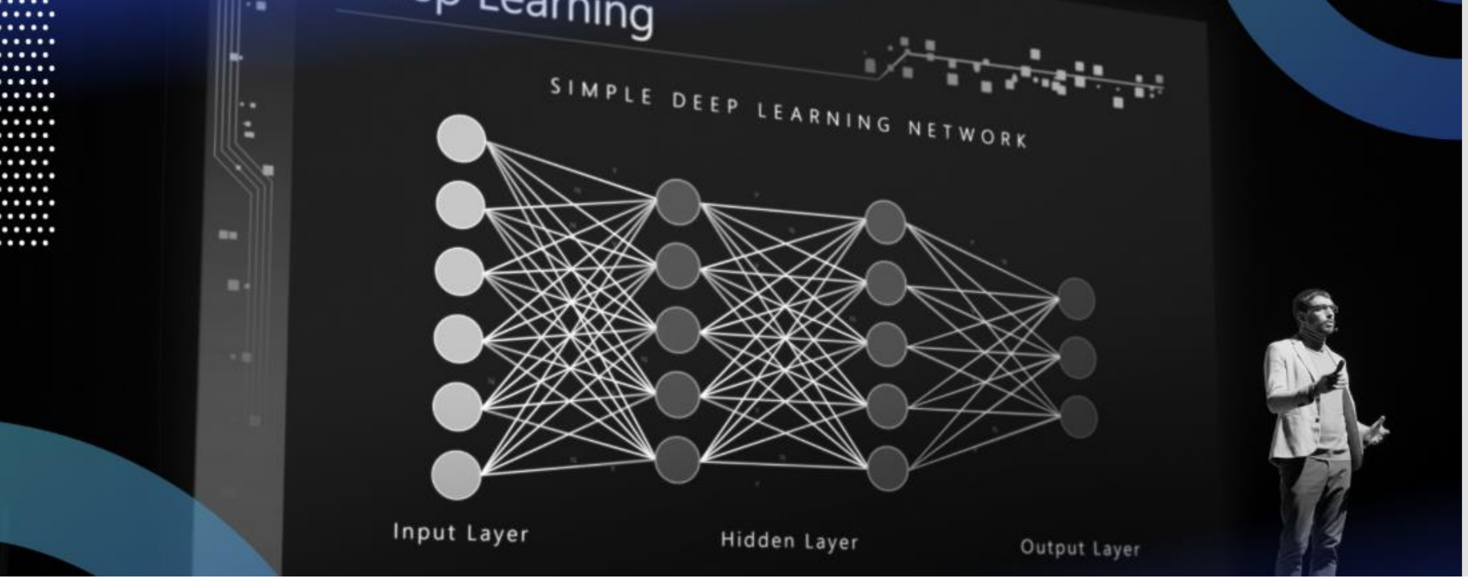
THE PROBLEM

Binary emotion classification from EEG signals

Distinguishing between focused and unfocused/drowsy cognitive states using labeled EEG data.

Real-world applications:

- Driver monitoring systems
- Attention assessment
- Human-computer interaction



The Problem

Binary Classification Task

Distinguish between focused and unfocused mental states using EEG signals

Deep Learning Approach

Building on Lab 1 Supervised learning's traditional ML methods with neural network architectures

Performance Goal

Compare deep learning effectiveness against conventional machine learning techniques

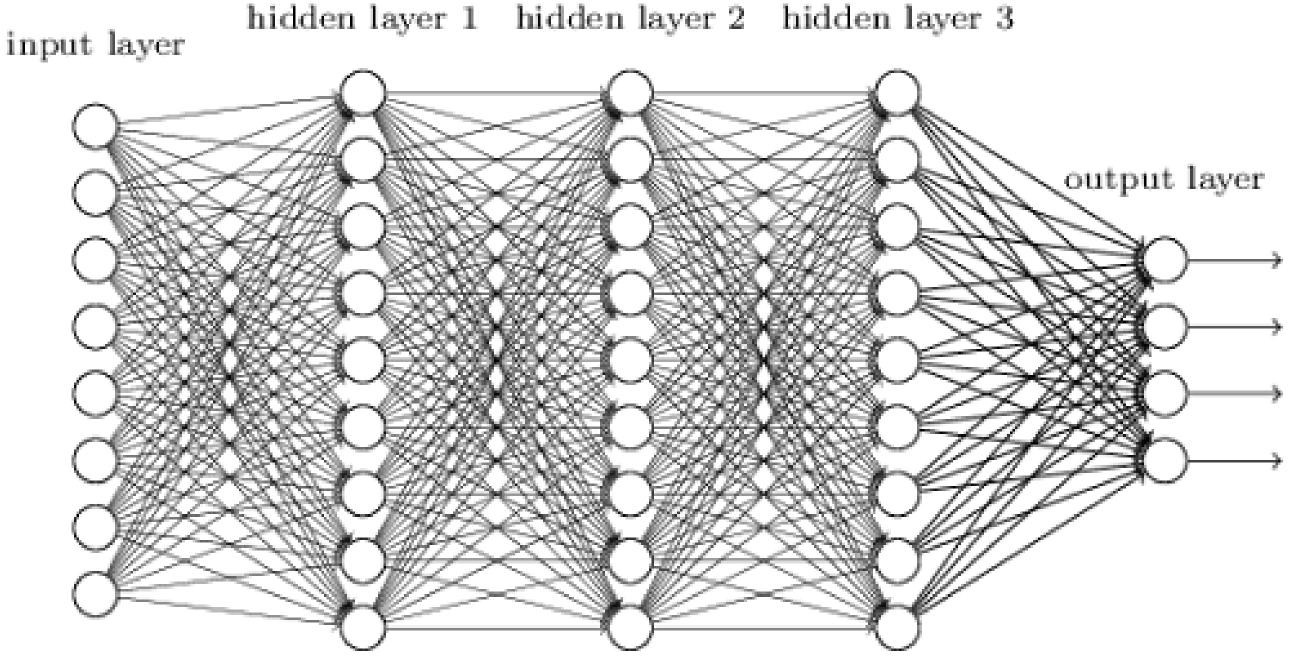
Real-world applications:

- Driver monitoring systems
- Attention assessment
- Human-computer interaction

Why Deep Learning?

Deep Learning Advantages

- **Automatic Feature Learning**: No manual feature engineering required
- **Pattern Discovery**: Can identify hidden patterns in complex data
- **Non-linear Modeling**: Captures complex relationships between features
- **Spatial Preservation**: CNNs maintain structural information
- **Scalability**: Performance improves with more data



Deep neural networks offer a fundamentally different approach to EEG analysis. Rather than relying on domain expertise to craft features, these models learn hierarchical representations directly from the data, potentially uncovering patterns that traditional feature engineering might overlook.

DATASET: SEED-IV

Shanghai Jiao Tong University

Key Dataset Characteristics

The SEED-IV (SJTU Emotion EEG Dataset) is a comprehensive collection of electroencephalogram recordings designed for emotion recognition research. This dataset provides a robust foundation for supervised learning experiments in affective computing.

15
Subjects
Diverse participant pool

3
Sessions
Per subject

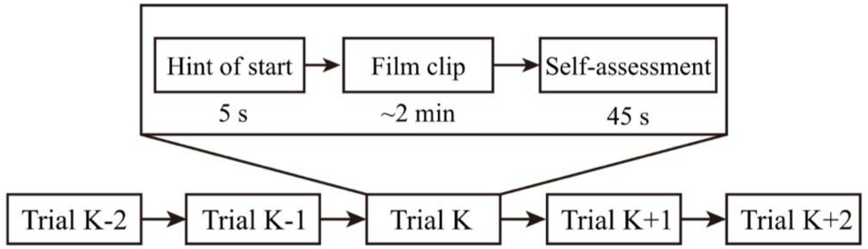
24
Trials
Per subject

62
Channels
EEG electrodes

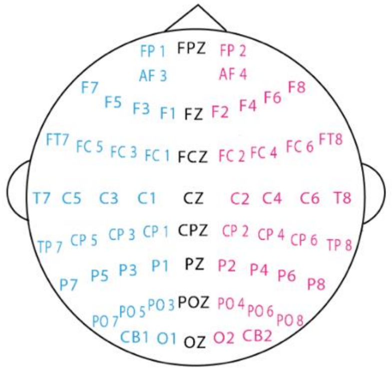
128
Hz
Sampling frequency

~2
Minutes
Per trial duration

Source: https://bcmi.sjtu.edu.cn/home/seed/seed-iv.html

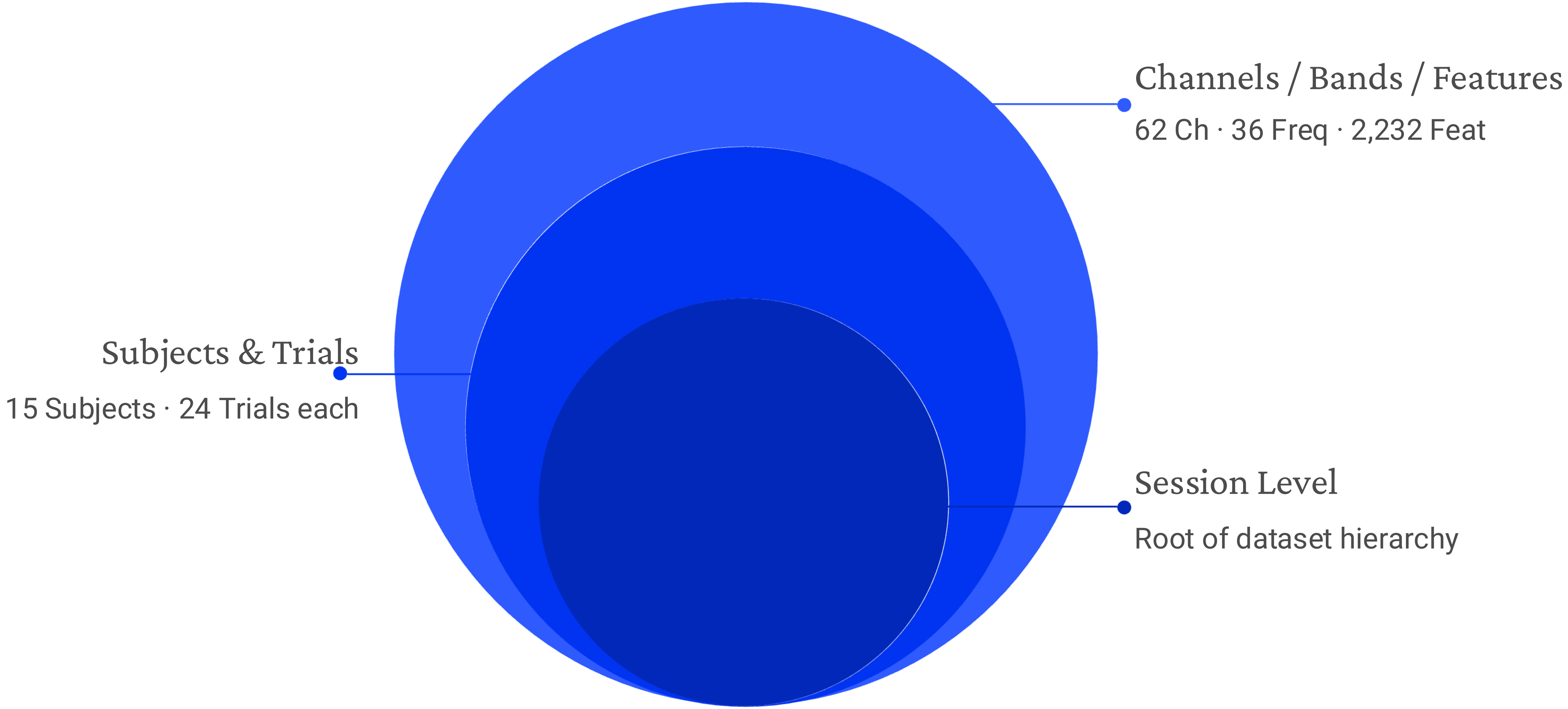


The experimental scene and the corresponding EEG electrode placement are shown in the following figures.



Citation: Zheng, W. L., & Lu, B. L. (2015). Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks. IEEE Transactions on Autonomous Mental Development.

DATA STRUCTURE



02

Exploratory Data Analysis

SEED-IV dataset structure, feature extraction, and key insights

EXPLORATORY DATA ANALYSIS

Class Distribution

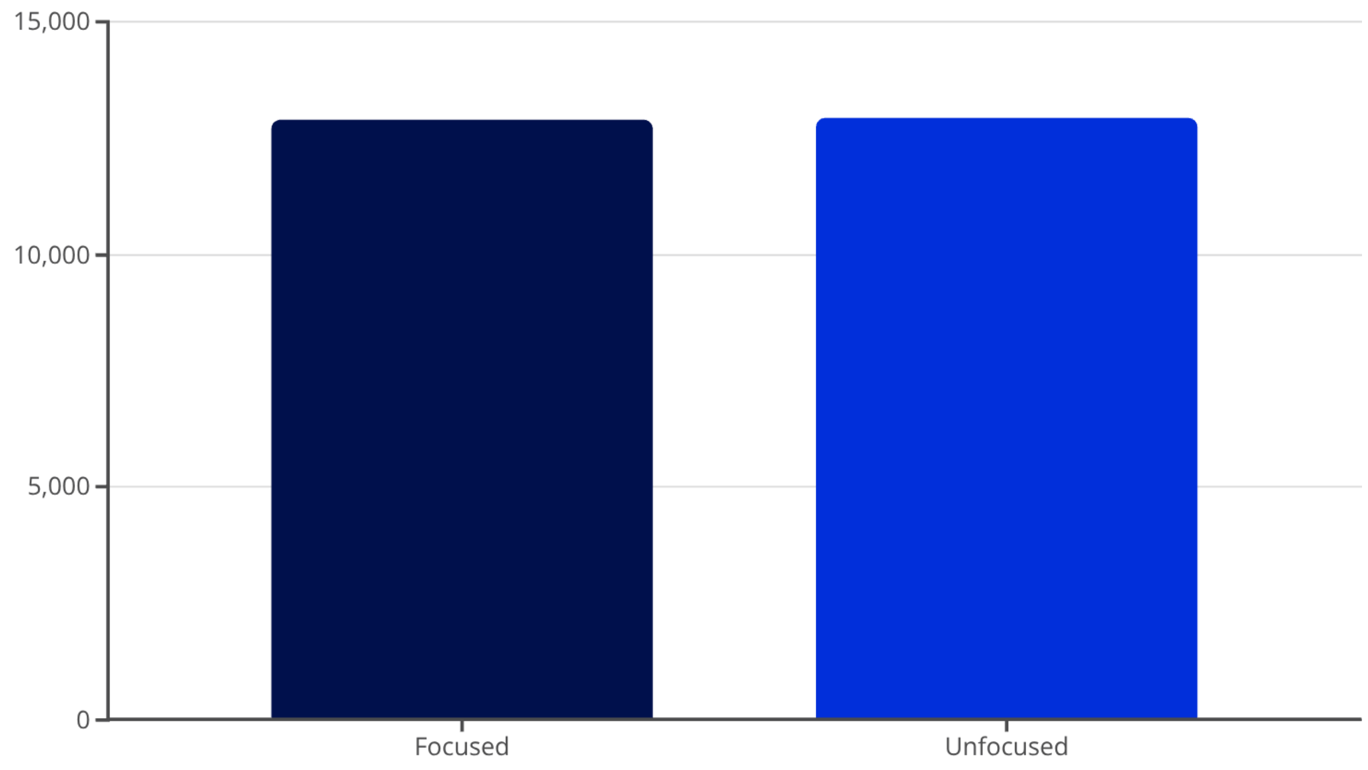
The SEED-IV dataset shows a well-balanced distribution of samples across the two key emotional states for analysis:

- **Focused (0):** 12,876 samples (49.9%)
- **Unfocused (1):** 12,918 samples (50.1%)

Total: 25,794 samples

Key Finding: Well-balanced distribution

This balanced dataset composition is crucial for training unbiased classification models and minimizes the need for aggressive resampling techniques, ensuring model performance metrics accurately reflect true predictive capability.



FEATURE STATISTICS

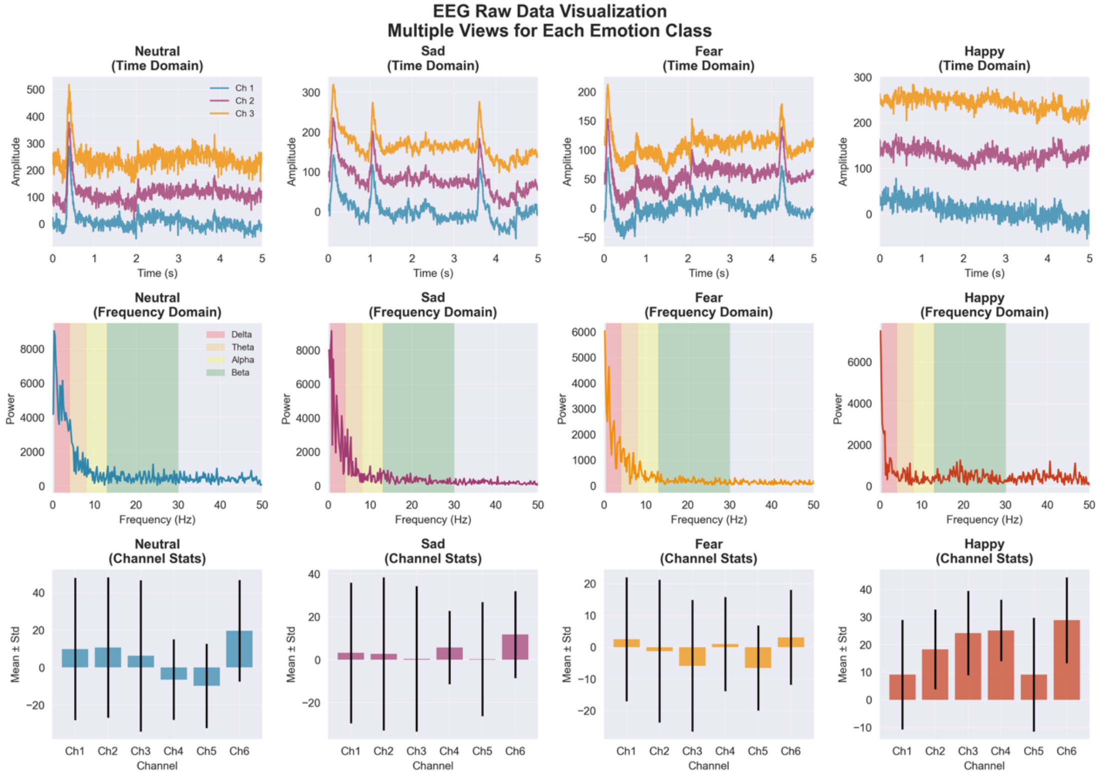
Total Features: 2,232 (62 channels × 36 frequency bands)

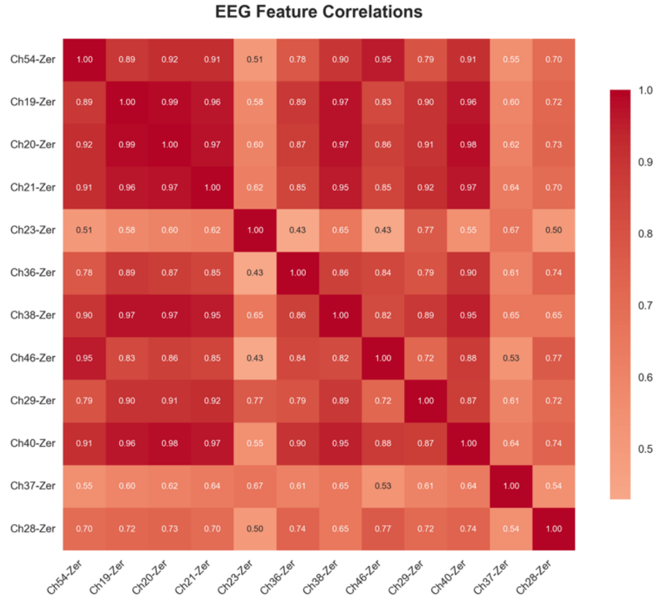
Statistics:

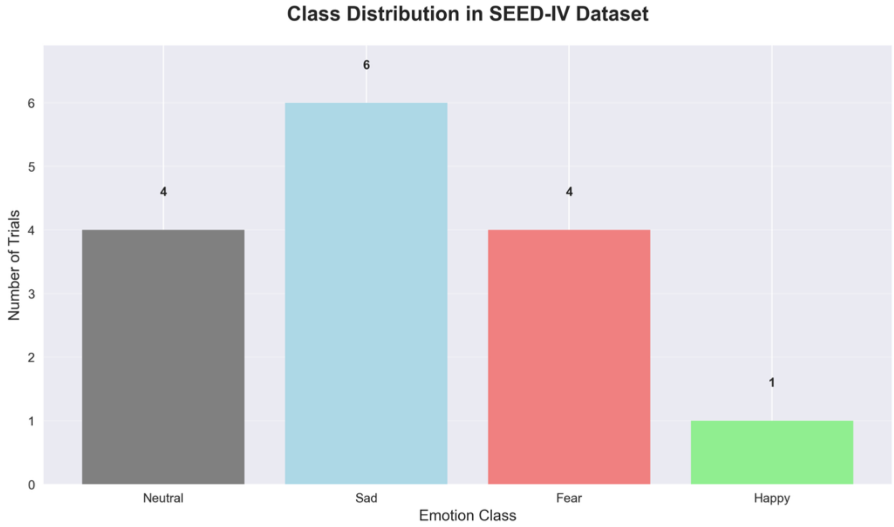
- Mean: -0.0000
- Std Dev: 1.0000
- Min: -3.8286
- Max: 7.3248
- Median: -0.0820

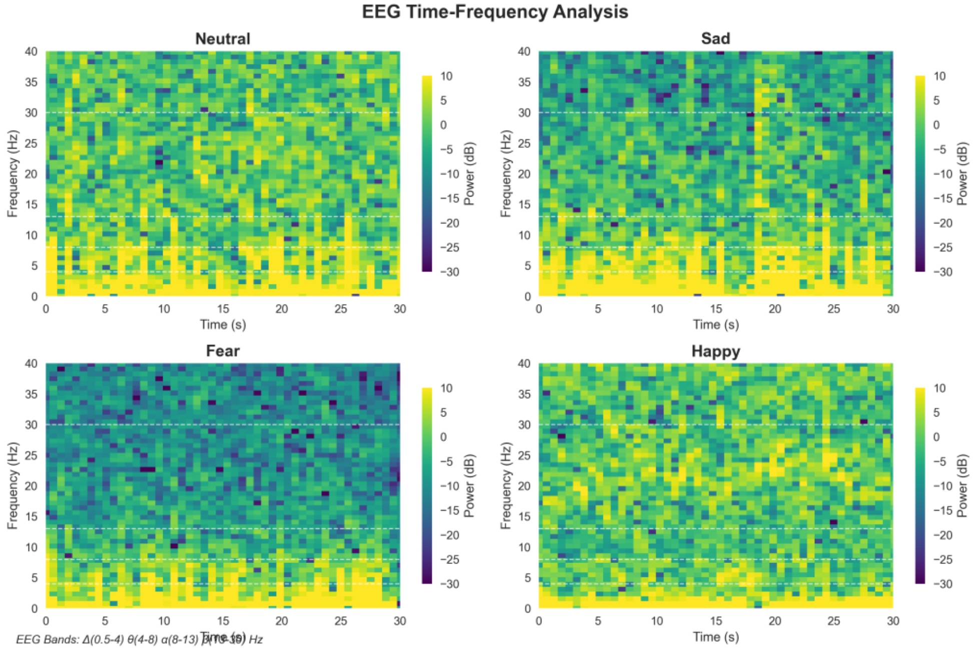
Features are standardized (StandardScaler)

Sample Data Visualization









Raw EEG Signal

Time-domain representation showing voltage fluctuations across a single channel, exhibiting characteristic brain wave patterns

STFT Spectrogram

Time-frequency representation revealing spectral energy distribution across the 4-40 Hz range

Theta (4-8 Hz)

Associated with drowsiness, meditation, and creative states

Alpha (8-13 Hz)

Dominant during relaxed wakefulness and closed-eye states

Beta (13-30 Hz)

Linked to active thinking, focus, and sustained attention

Gamma (30-40 Hz)

Related to higher cognitive processing and consciousness

EDA KEY FINDINGS

Well-balanced Classes

49.9% vs 50.1% distribution, indicating a balanced dataset for analysis.

Mean Correlation

0.47, which is within expected ranges for EEG signal processing.

Outlier Analysis

Only 2.05% of data points identified as outliers, within acceptable limits.

Data Completeness

Confirmed absence of missing or infinite values, ensuring data integrity.

Feature Variance

No constant features detected, crucial for model discriminative power.

Discriminative Frequencies

Frequency bands 4-40 Hz identified as containing key discriminative information.

Methodology Overview

My approach for EEG emotion deep learning training involves a clear progression from data preparation to deep learning architectures and hyper tuning, and finally model assessment.

Deep learning architectures

Training & Optimization

Evaluation

SEED-IV Dataset

2,232 features from 62 channels × 36 frequency bands

Deep Learning Architectures

Multi-Layer Perceptron (MLP) and Convolutional Neural Network (CNN)

Training & Optimization

Hyperparameter tuning with cross-validation

Performance Evaluation

Classification accuracy and comparison with Lab 1 traditional ML

Model Architectures Comparison

Multi-Layer Perceptron (MLP)

1. **Input Layer**
   2,232 flattened features
2. **Hidden Layer 1**
   512 neurons with ReLU
3. **Hidden Layer 2**
   128 neurons with ReLU
4. **Hidden Layer 3**
   32 neurons with ReLU
5. **Output Layer**
   2 classes (binary)

Convolutional Neural Network (CNN)

1. **Input Layer**
   1×62×36 (preserves 2D structure)
2. **Conv Layer 1**
   16 filters, 3×3 kernel
3. **Conv Layer 2**
   32 filters, 3×3 kernel
4. **Fully Connected**
   128 neurons with ReLU
5. **Output Layer**
   2 classes (binary)

Key Difference: The MLP treats all 2,232 features as a flat vector, while the CNN preserves the 2D spatial structure of 62 channels by 36 frequency bands, allowing it to learn local spatial patterns similar to image recognition.

Why CNN Architecture?

CNN Advantages

Spatial Preservation

Maintains relationships between EEG channels and frequency bands

Local Pattern Learning

Detects features across neighboring channels and frequencies

Weight Sharing

Parameter efficiency through convolutional filters

Translation Invariance

Recognizes patterns regardless of location

MLP Limitations

Spatial Structure Loss

Equal Treatment

Parameter Inefficiency

Limited Generalization

The CNN's architectural design is specifically suited for EEG data where spatial relationships matter. By treating the 62 channels by 36 frequency bands as a 2D spatial map, CNNs can learn local patterns between adjacent channels and frequency ranges, similar to how they detect edges and textures in images. This spatial awareness provides a significant advantage over traditional fully-connected networks that flatten these relationships.

EVALUATION STRATEGY

Leave-One-Session-Out Cross-Validation

Fold 1

Train: Sessions 2 & 3Test: Session 1

Fold 3

Train: Sessions 1 & 2Test: Session 3

1

2

3

Fold 2

Train: Sessions 1 & 3Test: Session 2

Why This Matters: This strategy prevents data leakage and ensures models generalize effectively across temporal boundaries and new recording conditions.

Hyperparameter Optimization

Search Space

Learning Rates

1e-4, 1e-3, 1e-2

Batch Sizes

16, 32, 64

Epochs

Up to 20 iterations

Optimizer

Adam with momentum

Optimal Configuration

1e-3

Learning Rate

Optimal balance between speed and stability

64

Batch Size

Best generalization performance

20

Epochs

Sufficient for convergence without overfitting

04

Results Overview

Performance comparison, findings, and future directions

Results Overview

Performance Analysis

Model Accuracy Comparison

Neural Network vs Convolutional Neural Network performance across all folds

Supervised Learning Benchmark Comparison

Deep learning vs traditional machine learning methods (SVM, Random Forest, Logistic Regression)

Detailed Classification Metrics

Confusion matrices, precision, recall, and F1-scores for both architectures

Per-Fold Performance Analysis

Consistency and generalization across different sessions

RESULTS

The evaluation process includes:

- Training both Neural Network and CNN models on each fold
- Calculating accuracy, precision, and recall metrics
- Generating confusion matrices for visual analysis
- Computing mean performance across all three folds
- Comparing results with Lab 1 traditional machine learning baselines

Note: The models are trained using the Adam optimizer with the optimal hyperparameters identified during the tuning phase. Each fold represents training on two sessions and testing on the held-out session to ensure robust generalization estimates.

Code examples

The evaluation process includes:

- Training both Neural Network and CNN models on each fold
- Calculating accuracy, precision, and recall metrics
- Generating confusion matrices for visual analysis
- Computing mean performance across all three folds
- Comparing results with Lab 1 traditional machine learning baselines

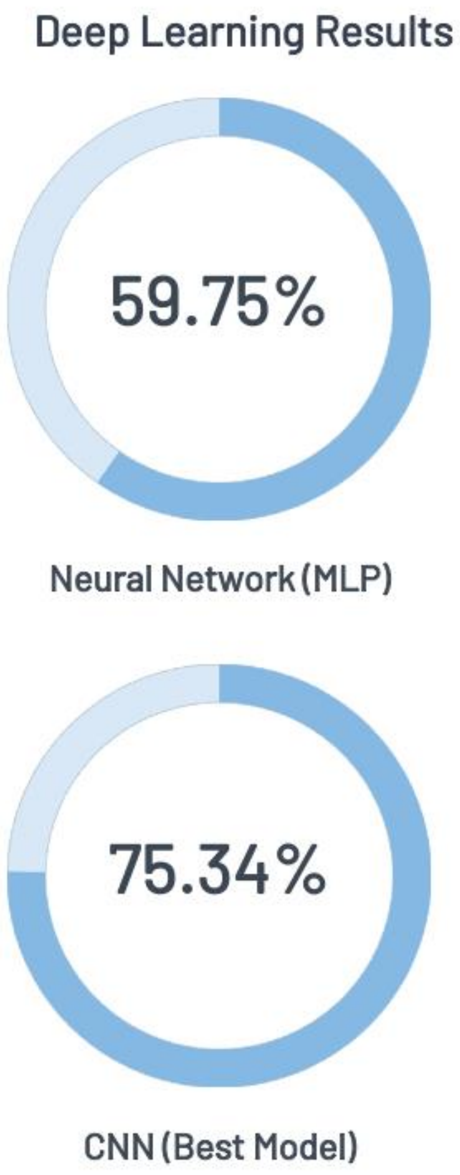
```python
# Create DataLoaders for batch processing
train_loader = DataLoader(train_ds, batch_size=batch_size, shuffle=True)
test_loader  = DataLoader(test_ds,  batch_size=batch_size, shuffle=False)

optimizer = torch.optim.Adam(model.parameters(), lr=lr)
loss_fn = nn.CrossEntropyLoss()  # Multi-class classification loss

for epoch in range(epochs):
    model.train()  # Set model to training mode
    total_loss = 0

    # Iterate over batches
    for batch_X, batch_y in train_loader:
        batch_X, batch_y = batch_X.to(device), batch_y.to(device)

        # Forward pass
        optimizer.zero_grad()
        logits = model(batch_X)
        loss = loss_fn(logits, batch_y)

        # Backward pass
        loss.backward()
        optimizer.step()

        total_loss += loss.item()
```

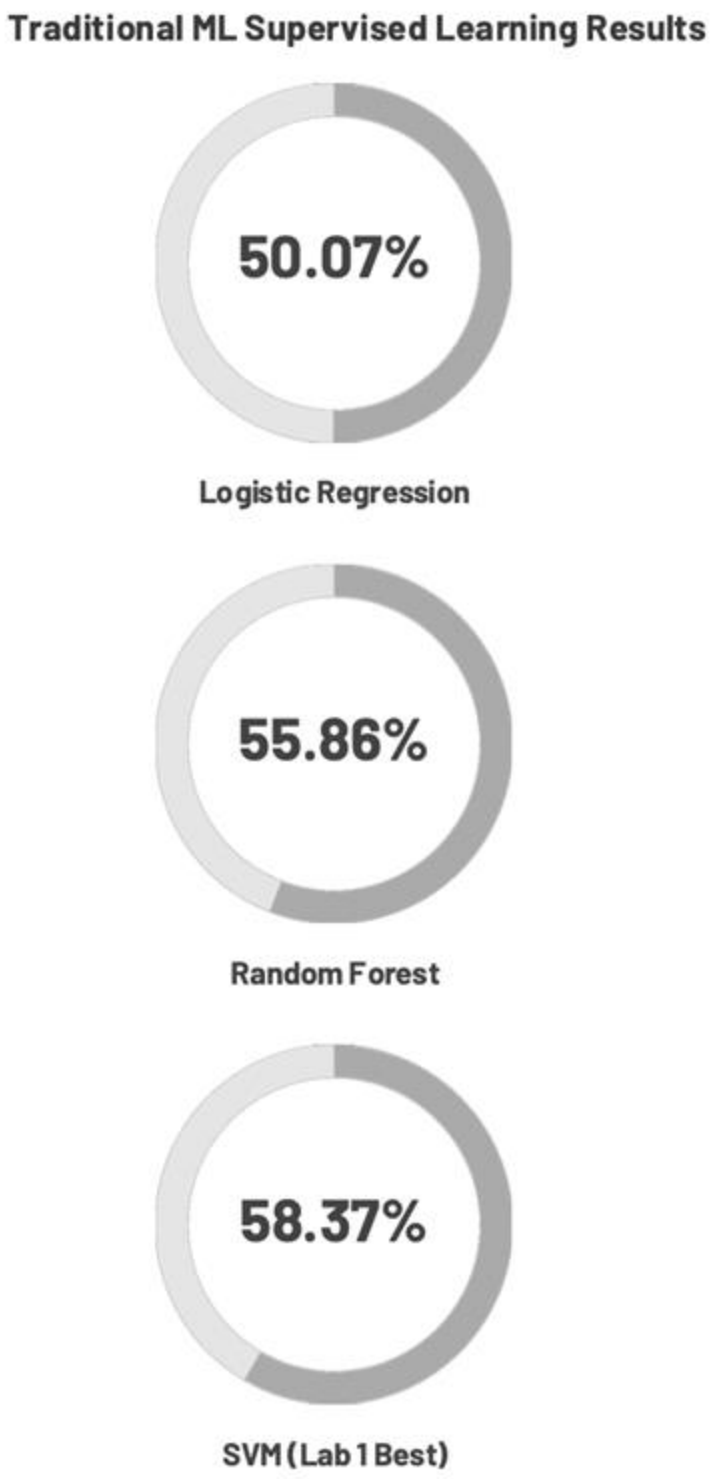
```python
class CNNClassifier(nn.Module):
    """
    Convolutional Neural Network for EEG emotion classification.
    """
    def __init__(self, num_classes=4):
        super().__init__()
        self.conv = nn.Sequential(
            nn.Conv2d(1, 16, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),    # Output: (16, 31, 18)

            nn.Conv2d(16, 32, kernel_size=3, padding=1),
            nn.ReLU(),
            nn.MaxPool2d(2),    # Output: (32, 15, 9)
        )

        self.fc = nn.Sequential(
            nn.Linear(32*15*9, 128),
            nn.ReLU(),
            nn.Linear(128, num_classes)
        )

    def forward(self, x):
        out = self.conv(x)
        out = out.reshape(out.size(0), -1)
        return self.fc(out)
```

```python
class NNClassifier(nn.Module):
    """
    Multi-Layer Perceptron (MLP) for EEG emotion classification.
    """
    def __init__(self, input_dim, num_classes=4):
        super().__init__()
        self.net = nn.Sequential(
            nn.Linear(input_dim, 512),
            nn.ReLU(),
            nn.Linear(512, 128),
            nn.ReLU(),
            nn.Linear(128, 32),
            nn.ReLU(),
            nn.Linear(32, num_classes)
        )

    def forward(self, x):
        return self.net(x)
```

(parameter) num_classes: int

Accuracy Comparison



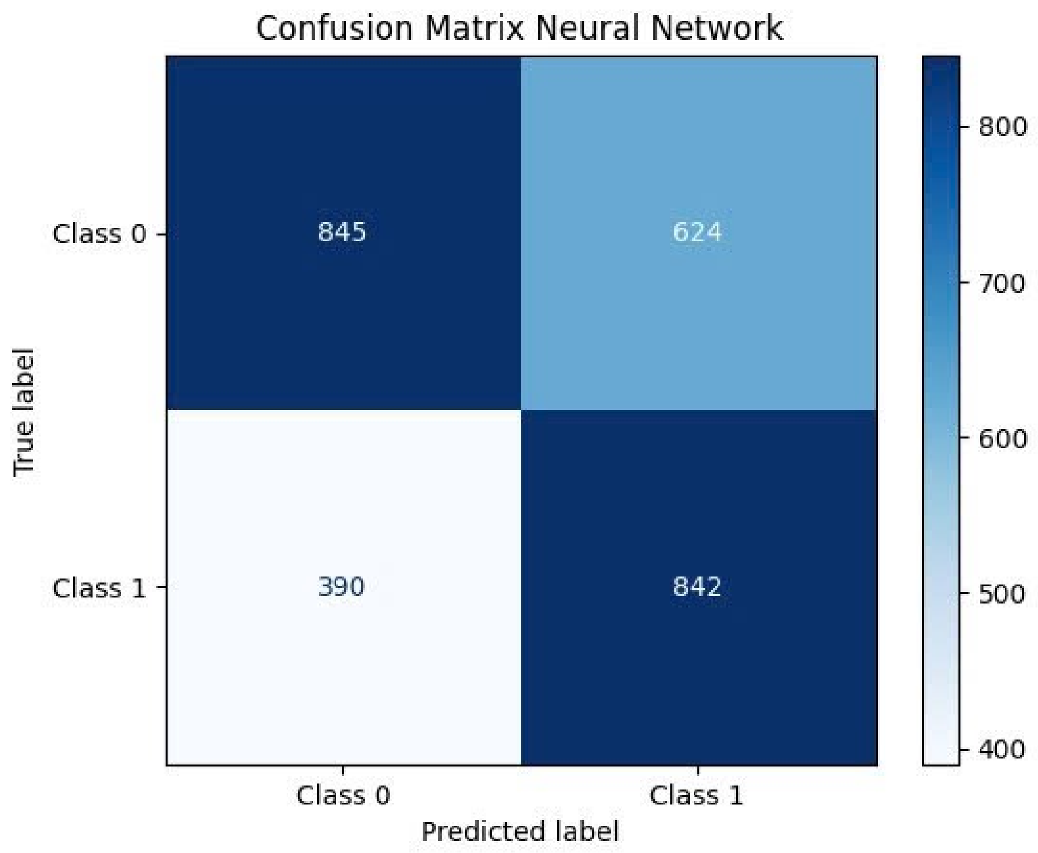


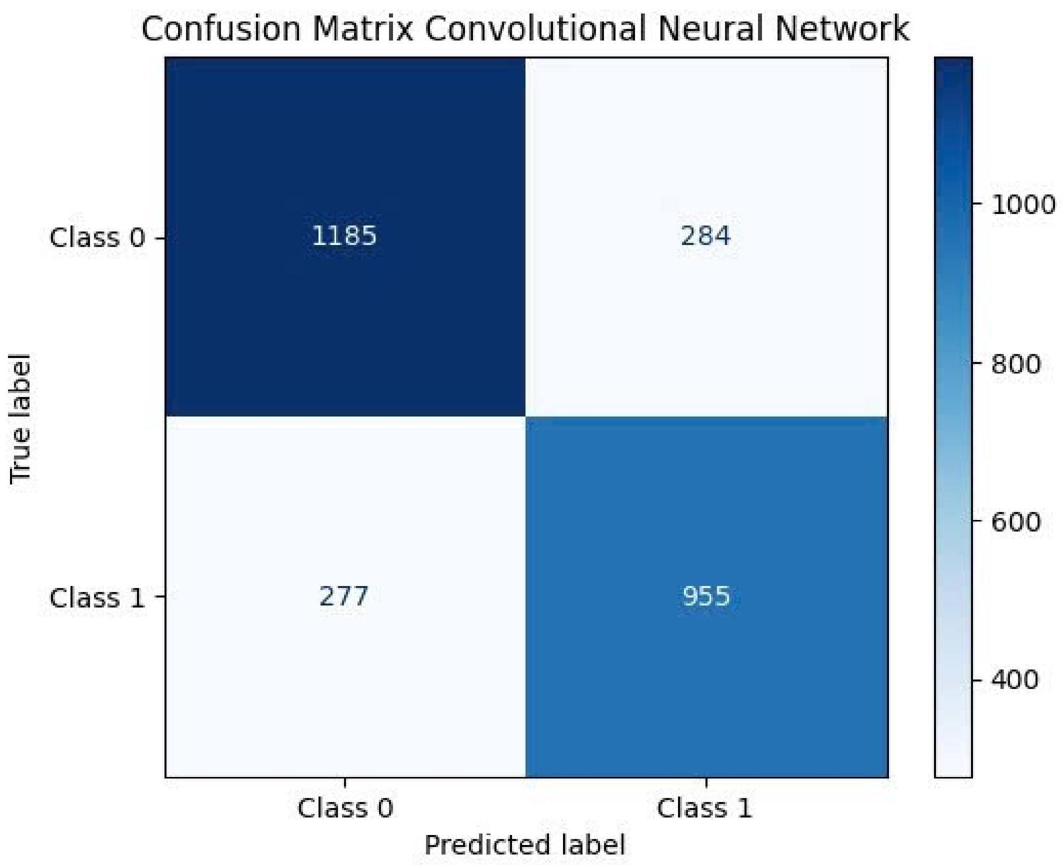
Per-Fold Performance Comparision

Model	Fold 1	Fold 2	Fold 3	Mean
Neural Network	59.76%	62.46%	57.02%	**59.75%**
CNN	**71.63%**	**79.23%**	**75.16%**	**75.34%**
Logistic Regression	45.73%	54.39%	50.10%	**50.07%**
SVM (RBF)	53.91%	60.64%	60.55%	**58.37%**
Random Forest	53.67%	53.91%	60.00%	**55.86%**

The CNN demonstrates **strong and consistent performance** across all three folds, with accuracies ranging from 71.63% to 79.23%. This relatively small variance (±3.8%) indicates robust generalization to different sessions and temporal conditions.

Confusion Matrices





Balanced Classification

Both models show relatively balanced performance across classes, avoiding bias toward either focused or unfocused predictions

CNN Superiority

The CNN's confusion matrix reveals significantly fewer misclassifications, with stronger confidence in correct predictions

Spatial Features Matter

The performance gap highlights the importance of preserving EEG channel relationships for accurate emotion recognition

Key Findings

CNN Achieved Best Performance

75.34% accuracy represents the highest classification accuracy across all models tested in both Lab 1 and Lab 3

Substantial Improvement Over Traditional ML

17 percentage point gain over Lab 1's best model (SVM at 58.37%), demonstrating deep learning's superior feature learning capabilities

Spatial Structure Preservation is Critical

CNN's 15.59% advantage over MLP proves that maintaining the 2D channel-frequency structure enables better pattern recognition

Automatic Feature Discovery Outperforms Engineering

Deep learning networks learn representations that surpass manually designed features, eliminating need for extensive domain expertise

Consistent Cross-Session Generalization

Strong performance across all three folds (71-79%) indicates robust learning that generalizes well to new recording sessions

Why CNN performed best in EEG case?

CNN Advantages

Spatial Preservation

Maintains relationships between EEG channels and frequency bands

Local Pattern Learning

Detects features across neighboring channels and frequencies

Weight Sharing

Parameter efficiency through convolutional filters

Translation Invariance

Recognizes patterns regardless of location

MLP Limitations

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Limited Generalization

The CNN's architectural design is specifically suited for EEG data where spatial relationships matter. By treating the 62 channels by 36 frequency bands as a 2D spatial map, CNNs can learn local patterns between adjacent channels and frequency ranges, similar to how they detect edges and textures in images. This spatial awareness provides a significant advantage over traditional fully-connected networks that flatten these relationships.

Deep learning vs Supervised learning: Deep Dive Comparison

Key Insight: Deep learning's automatic feature discovery significantly outperforms traditional approaches when the data has inherent structure to exploit. The 17% improvement comes at the cost of increased computational requirements and reduced interpretability, but the performance gains make this trade-off worthwhile for many applications.

Traditional Machine Learning (Lab 1)

Best Model: SVM

58.37% accuracy

Approach

Hand-crafted features with extensive domain expertise required

Training Speed

Fast training on conventional hardware

Interpretability

Feature importance easily analyzed

Deep Learning (Lab 3)

Best Model: CNN

75.34% accuracy

Approach

Automatic hierarchical feature learning from data structure

Training Speed

Requires more compute and time

Interpretability

Less transparent (black box)

+17%

Accuracy Improvement

CNN over SVM

0

Feature Engineering

Hours saved with automatic learning

15.59%

Structure Matters

CNN gain over MLP

Limitations

Computational Resource Requirements

Deep learning models demand significantly more GPU memory, training time, and computational power compared to traditional ML algorithms. Training can take hours instead of minutes.

Reduced Interpretability

Neural networks operate as "black boxes"—understanding *why* a prediction was made is challenging. Feature importance and decision boundaries are not as transparent as in traditional ML.

Architecture Not Fully Optimized

The current CNN design, while effective, could potentially be improved with deeper networks, attention mechanisms, or more sophisticated convolutional structures tailored specifically for EEG topology.

Temporal Dynamics Underutilized

The current approach doesn't fully capture temporal patterns in EEG sequences. Time-series modeling with RNNs or temporal convolutions could further enhance performance.

Future Work

Hybrid CNN-RNN Architectures

Combine CNNs for spatial feature learning with Recurrent Neural Networks (LSTMs or GRUs) to capture temporal dependencies in EEG sequences. This would leverage both spatial and temporal patterns simultaneously.

Attention Mechanisms

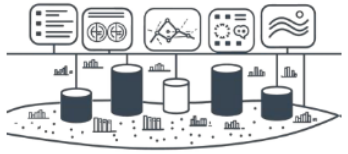
Implement attention layers to automatically identify and weight the most informative EEG channels and frequency bands for emotion classification. This could improve both performance and interpretability.

Transfer Learning Strategies

Pre-train models on large EEG datasets and fine-tune for specific subjects or tasks. This could enable personalized emotion recognition systems with minimal subject-specific training data.

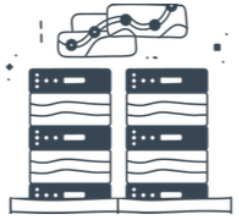
Data Augmentation Techniques

Apply EEG-specific augmentation methods like time-shifting, frequency masking, or synthetic sample generation to increase training data diversity and model robustness.



Advanced Temporal Modeling

Explore temporal convolutional networks (TCNs) or Transformer architectures specifically designed to model long-range dependencies in time-series EEG data.



Graph Neural Networks

Represent EEG channels as graph nodes with edges weighted by physical proximity or functional connectivity, allowing GNNs to learn from brain network topology.

Conclusion

75.34%

CNN Achieves Best Performance

Deep Learning Superiority	17% Improvement	Spatial Structure Matters
CNN significantly outperforms all traditional ML methods with 75.34% accuracy	Substantial gain over Lab 1's best model (SVM: 58.37%)	Preserving 2D channel-frequency relationships is crucial for EEG classification

This project successfully demonstrates that deep learning approaches, particularly Convolutional Neural Networks, can significantly outperform traditional machine learning methods for EEG emotion classification.

Key Takeaway: When data has inherent spatial or structural properties, architectures that preserve and leverage this structure (like CNNs for spatial data or RNNs for temporal data) will substantially outperform approaches that treat features as independent, flattened vectors.

GitHub Repository: Complete code, analysis, and detailed results available for review and reproduction
https://github.com/kieumyaidev/lab-3

Reference

1. Dataset
- **SEED-IV Dataset**: https://bcmi.sjtu.edu.cn/home/seed/seed-iv.html

2. Key Concepts and Methods from CU Boulder's Deep Learning Course Note

AI ACKNOWLEDGMENTS

I would like to acknowledge the use of AI tools in the development of this project:

Cursor: Used for debugging code and resolving technical issues during implementation and helping to populate the README file after I finish my work

ChatGPT: Assisted with restructuring and proofreading content. I provided the overall structure and bullet points for each section, and ChatGPT helped with minor language revisions and proofreading to improve clarity and flow

Gamma AI: Used for formatting presentation slides. The content of the slides was derived from this notebook, and Gamma AI assisted with the visual layout and formatting

All core concepts, methodology, experimental design, analysis and presentation content are my own work. The AI tools were used primarily for code debugging, language refinement, and presentation formatting assistance.

THANK YOU

Questions?

This presentation covered deep learning approaches for EEG emotion classification, including exploratory data analysis, methodology design, model evaluation, and future directions.

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